Mutual Fund Industries in Emerging Markets: Evidence from China

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requirements for the Degree of
Doctor of Philosophy in Finance

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Abstract

There are three aims in this thesis: the first is to test, in the context of the Fama and French Five-Factor-Model, what combination or combinations of factors best explain the stock return variations in China. The second is to test, through two sensitivity analyses, whether the factors' explanatory power can be increased significantly by redefining their cutting points or by adopting different factor construction methods. And finally, to test whether analysing mutual fund performance using the different models produces fundamentally different conclusions about funds' performance.

To serve these purposes, we set up five chapters. Chapter 1 gives an introduction and reviews literature on the material discussed in chapters 2 through 5. Chapter 2 tests various combinations of factors specified in the Fama and French Five factor model and investigates what combinations of factors best explain the stock return variation in our study period. Chapter 3 contains two sensitivity analyses which test whether 1) by redefining cut-points for the size factor produces a factor with significantly different explanatory power; 2) by adopting different factor construction methods, whether significantly different size and value factors can be produced. In chapter 4, we use various traditional capital asset pricing models, in particular, the CAPM model, our optimal model found in chapter 2, Fama and French Three factor model and the Fama and French Five factor model, to examine the Chinese equity mutual fund performance. Finally, in chapter 5, we give our conclusions and limitations of this research.

We decided, based on chapter 2, that the model consisting a market and a size factor fares best in the Chinese A-Share stock market. This decision was made based on a number of considerations including the adjusted R-Squared, the trade-off between the adjusted R-Squared and the multicollinearity problems, the *GRS* test and the data credibilities. Chapter 3 indicates that various cutting

points and different methods of factor constructions do not influence the factors' explanatory power significantly. More interesting are the findings in chapter 4: using our optimal model containing a market and a size factor, the risk-adjusted return is much lower than the other factor models. This result was robust when we split our study period into two sub-periods.

Introduction and Thesis Statement

Ever since the critique of the CAPM starting from the 1970s (Roll, 1977; Black et al., 1972; Fama and MacBeth, 1973; Banz, 1981; Stambaugh, 1982; Bondt and Thaler, 1985; Bhandari, 1988; Jegadeesh and Titman, 1993; Fama and French, 2004), a number of empirical researchers have been working on factor-style asset pricing models which are aimed at explaining the extra patterns in the stock-return variations left unexplained by the market portfolio alone. These include: the Fama and French (1992) three-factor model (FF3), which added the size and the book-to-market factors onto the original CAPM; the Carhart (1997) four-factor model (Carhart4), which added an momentum factor to the FF3; and most recently, the Fama and French (2015) five-factor model (FF5), which augmented the FF3 with two additional factors – the investment-style and the profitability factors. Among them, the FF3 received most academic credit[1], but all models were applied widely around the world, especially in the area of evaluating the performance of equity mutual funds (Fama and French, 1993; Elton et al., 1996; Białkowski and Otten, 2011; Laes and da Silva, 2014).

The application of these models to the evaluation of the performance of a equity mutual fund is straight forward: mutual fund managers often claim to have superb stock-picking abilities and hence they charge fees to investors for having the access to such ability which is otherwise unobtainable and unknown to investors. However, a factor-style asset pricing model makes it known to the public exactly what characteristics of stocks explain why a stock generates a high or a low return. Once we take into account the characteristics of stocks that a fund manager holds, that is, after deducting the extra (either positive or negative) returns a stock with certain characteristics carries, we derive at a risk-adjusted

[1]Eugene Fama, Robert Shiller and Lars Peter Hansen received a Nobel Price in Economic Sciences in 2013 for their empirical analysis of asset prices.

return of a fund which reflects the real return a manager generates, hence the real ability of a manager to pick stocks.

While these models are useful, one can argue that because they were created using data from only the US market, they may not be suitable for a capital market that is fundamentally different from the one in the US, for example the Chinese market. The Chinese market is different from the US capital market in many ways, it was transformed from a communist state-owned economy directly to a socialism-styled capital market within which all firms were listed on the stock exchange directly without the normal growth trajectory that firms in the US would otherwise take. Therefore, factors explaining the Chinese stock-return variation may be different from the ones for the US market.

Further more, there are a number of unique market characteristics that may affect the factors in China. For example, board of directors' military back ground affects stock returns (Fan et al., 2007); frequent change of accounting standards especially during the period of financial market reforms (Firth et al., 2011), which render accounting figures inconsistent in different time periods.

In this thesis, we investigate two things. First, we examine the five factors in the FF5 and ask, what subset(s), if any, of factors best explain the stock-return variations in China. Second, once the optimal set of factors is determined for this market, we will then further test whether redefining the definitions of characteristics will change our model's explanatory power. In particular, using the size factor as an example, while FF3 constructed the SMB factor by deducting return of portfolio consists the top 50% biggest stocks from the return of portfolio consists the bottom 50% smallest stock, we will test whether defining small stocks as the bottom 10%, 20%, 30%, 40%, 50%, 60%, 70%, 80%, and 90% of all stocks will create a factor that is significantly different from a factor that is constructed using the FF3 and FF5 standard construction method.

There are papers looking at answering our first question (Lihui et al., 2014; Hu et al., 2019; Liu et al., 2019), but most of them focus on FF3 only owing to the fact FF5 is fairly new (2015). As for our second question, even though there are papers looking at alternative factor definition, for example Liu et al. (2019), no one has considered it from the view of changing the cutting points. The closest study on this issue is Liu et al. (2019) which eliminated the bottom smallest 30% stocks before constructing the size factor.

We set up our five chapters in this thesis as follows: Chapter 1 gives an introduction and reviews related literature on the material discussed in chapters 2 through 5. Chapter 2 tests various combinations of factors specified in Fama and French Five factor model and investigates what combinations of factor best explain the stock return variation in our study period. Chapter 3 contains two sensitivity analyses which test whether 1) by redefining cut-points for the size and value factors produce factors with significantly different explanatory power; 2) by adopting different factor construction methods, whether a significantly different set of factors can be produce. In chapter 4, we used various traditional capital asset pricing models, in particular, the CAPM model, our optimal model found in chapter 2, Fama and French Three factor model and the Fama and French Five factor model, to examine the Chinese equity mutual fund performances. Finally, in chapter 5, we give conclusions and limitations of this research.

1. Introduction and Literature Review

1.1 A Brief History and Development of the Capital Asset Pricing Model

1952 – the year of Markowitz's publication on portfolio selection (Markowitz, 1952) marks the initiation of the classic asset pricing models. Provided with theoretical fundamentals, scholars (Sharpe, 1964; Lintner, 1965; Mossin, 1966) soon proposed the capital asset pricing model (CAPM), which for the first time enabled them to quantify the relationship between the risk and return of an asset. The simplicity of the theoretical framework of the model was ingenious. However, since it was based on a large number of assumptions, especially the assumption that the market was efficient and market participants are able to borrow and lend freely at the risk-free rate, the model soon attracted a number of critiques.

Faced with a plethora of evidence found within the first 20 years of the founding of the model (Roll, 1977; Black et al., 1972; Fama and MacBeth, 1973; Banz, 1981; Stambaugh, 1982; Bondt and Thaler, 1985; Bhandari, 1988; Jegadeesh and Titman, 1993; Fama and French, 2004), scholars in the field of finance started to look for ways to either fix or alter the model.

In this section, we first describe the birth and the development of the CAPM model. Then, we illustrate the model's underlying assumptions and the critiques it has received. Finally, we examine a range of solutions proposed by researchers.

1.1.1 A Brief History of the Efficient Market Portfolio Theory and Its Applications

The publication of Markowitz (1952) followed by Sharpe (1964) and Lintner (1965) was the initiation of modern portfolio theory. Before the appearance of these papers, the field of finance consisted of several major aspects, such as predicting firms' future returns using accounting data, cash flow analysis and credit ratings. Although it was well known for a long time that an asset has a return as well as a risk (Lowenfeld, 1909), nobody was able to quantify the relationship between risk and return. Markowitz, in his paper, for the first time was able to demonstrate that assets' return, once treated as a stationary Brownian motion process, could be estimated based on the law of large numbers. Further, the variance of a portfolio of assets could be reduced by including a large number of assets in the portfolio (Solnik, 1974).

Figure 1.1 demonstrates the relationship between a portfolio's estimated return and variance on the minimum-variance frontier, which is the foundation of the later CAPM and also a useful tool in portfolio selection. The curve CA illustrates Markowitz's minimum-variance frontier. We can look at these portfolios on the curve in two ways: 1) these portfolios' variances are minimized given the expected returns, 2) the portfolios' expected returns are maximized given the level of risk (expressed using variance). Investors should hold portfolios that are on the curve for the highest ratio of return to risk. Of course, the exact point to choose on the curve depends on individual investors' risk preferences. Based on this demonstration, Sharpe and Lintner (Sharpe, 1964; Lintner, 1965) added

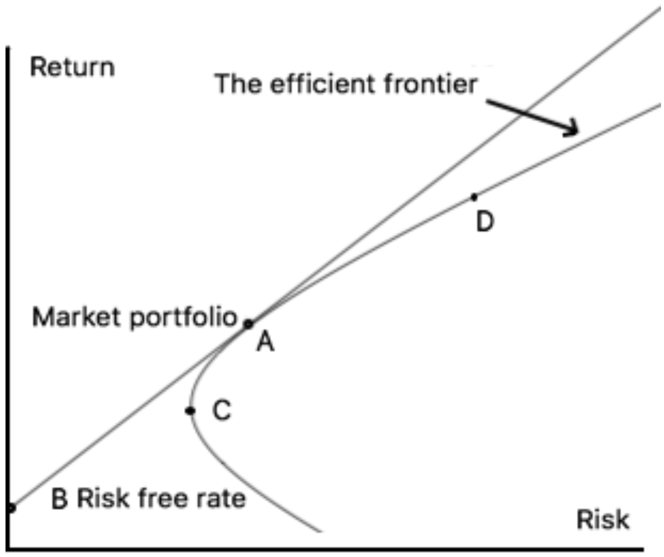


Figure 1.1: Markowitz Mean-Variance Frontier.

two more assumptions which added a straight line (BA) to Markowitz's minimum variance frontier in Figure 1.1, which is the framework of the CAPM. The two assumptions are there is only one risk-free rate which investors can borrow and lend freely at, and everyone in the market has full knowledge about the price and the same expectations on distributions of assets' returns. The second assumption means everyone in the market will hold the same portfolio, therefore the market portfolio. The exact location of the market portfolio on the efficient frontier is point A – the tangent point on the efficient frontier that connects to the risk-free rate. Therefore, the line BA becomes the capital market line on which all investors choose a combination of the risk-free asset and the market portfolio. Investors will choose to hold a portfolio along the line depending on their risk-aversion levels. For example, the most risk-averse investor will choose to hold portfolios at point B since it is the risk-free portfolio. The less risk-averse investors will hold portfolios further up on the line since those assets are riskier.

The return and risk (variance) are the two most importance aspects that define a portfolio. The expected return of a portfolio is denoted as $E(R_p) = \Sigma w_i E(R_i)$ where R_p is the return of the portfolio, R_i is the return on asset i and w_i is the weight of asset i. The variance of the portfolio is denoted by $\sigma_p^2 = \Sigma w_i^2 \sigma_i^2 + \Sigma\Sigma w_i w_j \sigma_i \sigma_j \rho_{i,j}$ where σ_p, σ_i and σ_j are the standard deviations of historical returns of the portfolio, the asset i and asset j and $\rho_{i,j}$ is the correlation coefficient between the returns of asset i and j. The total risk measured by the standard deviation can be decomposed into systematic risk and non-systematic risk. Diversification can reduce non-systematic risk and therefore reduce the total risk while keeping the expected return at the same level. In other words, investors holding a portfolio instead of holding a single stock can theoretically gain the same level of return but significantly reduce the risk of their investment. Faced with the same level of expected return, a portfolio will give an investor a lower risk. Markowitz along with Merton Miller and William Sharpe were awarded the Nobel Prize in Economics in 1990, which shows the importance of their combined work in modern portfolio theory.

From Markowitz's Portfolio Selection to the CAPM – An Important Assumption behind the CAPM

Markowitz's efficient frontier is an ingenious work that demonstrates the relationship between the returns and risks of all possible assets in a market. The efficient frontier was created using the combination of the assets with the two highest Sharpe ratios[1] in the market. Therefore, all the efficient combinations of assets lie on the efficient frontier. It was clear that any rational investors would choose to hold an asset along the efficient frontier if he or she decided to hold risky assets. However, during the first few years after Markowitz's publication (1952), it was not clear to scholars that the tangent point is in fact the market portfolio.

[1] A Sharpe ratio (Sharpe, 1966) of an asset is the average excess return divided by standard deviation of the asset's excess return. It gives the excess return per unit of risk.

The tangent line is the line connecting the risk-free rate and the tangent point. Given different levels of the risk-free rate, the tangent point can be any point on the upper part of the efficient frontier. Only when the risk-free rate is fixed and every one in the market has the same expectation on assets' return distribution and risk, is there only one tangency point. This tangency point is effectively the market portfolio. Interestingly, it was the assumption that the tangent point is the market portfolio which received a large number of critiques. The following section describes the assumptions behind the CAPM.

The assumptions behind the CAPM

The model is based on a large number of strong assumptions which attracted critiques:

1. The model assumes that investors are rational and are risk-averse.

The model ignores the fact that not all investors are rational and some investors may take more risk for low expected returns due to their utility functions. For example, a gambler betting on a big-wheel outcome for the pleasure of it as well as expected returns. The expected return for the given risk is low, but the gambler does not mind. Their gambling is partially for the pleasure they get from betting at the table (Conlisk, 1993).

2. Investors are price takers, i.e., they cannot influence prices.

This assumption ignored the institutional investors, such as pension funds, mutual funds, or hedge funds. For example, traders of large mutual funds often buy and sell assets in large quantities. When they trade at large volume, they often influence the prices in the market. In these cases, they are not purely price takers.

3. Investors can lend and borrow unlimited amounts at the risk-free rate of interest.

In reality, borrowing and lending are at different rates and limited.

4. Investors can trade without transaction costs. That is, there were no trading costs, such as administration fees or taxes.

This assumption was necessary to allow the return of every investor to fall on the capital market line – the line that crosses the risk-free rate and the tangent point on the minimum variance curve. However, investors, especially individual investors, experience high transaction costs. Recognizing the trading cost would actually move the investors away from the capital market line.

5. The securities are highly liquid.

This assumption invalidates the CAPM in a similar way to the last assumption. In reality, not all assets are highly liquid. For example, large buildings or real estate take time to trade and often incur significant costs during trading. Sellers may also take a long time to find a suitable buyer. During the time of waiting, a number of different costs may be incurred, such as legal fees or maintenance fees. These costs again distort the investors' returns away from the capital market line.

6. Investors have homogeneous expectations about assets' returns.

The CAPM assumes that investors have the same expectations about the returns of all assets. In reality, people have different beliefs about the prices of assets in the next period.

7. All information is available at the same time to all investors and investors use the information to make informed decisions.

Although the credit for the CAPM was always given to the combined three scholars of Sharpe, Lintner and Mossin (Mossin, 1966), credit should also be given to Treynor (Treynor, 1961, 1962) who proposed the original ideas of the CAPM. However, since Treynor's papers were not actually published but were circulated among scholars, they were often disregarded as the initiation of the CAPM. In his 1962 paper (Treynor, 1962), Treynor put forward the assumptions for the original asset pricing model to work: no taxes (assumption number 4), no market frictions, ignoring transaction costs (assumption number 4), investors maximize their reward-to-risk ratio (assumption number 1), investors are risk-averse (assumption number 1), lending and borrowing are possible at the same interest rate (assumption number 3), securities can be traded in any amount (assumption 2 and/or 5) and investors have the full knowledge of the market (assumption number 7). His model was the first to develop the linear relationship between the expected return and the covariance with the market portfolio. Most importantly, his papers were the first to claim that the market portfolio was the single optimal mean-variance portfolio to hold in equilibrium (French, 2003).

1.1.2 The Era of Critique

Since its discovery, the CAPM model has been widely used in applications such as estimating firms' cost of capital or analyzing the performance of managed portfolios (Fama and French, 2004). Studies found a number of problems surrounding the theory, including the difficulty of testing, endogeneity or circularity, and empirical evidence that invalidates the CAPM (Roll, 1977; Black et al., 1972; Fama and MacBeth, 1973; Banz, 1981; Stambaugh, 1982; Bondt and Thaler, 1985; Bhandari, 1988; Jegadeesh and Titman, 1993; Fama and French, 2004). In this section, we discuss these problems in detail.

Firstly, theoretically, Roll (1977) explained that it is impossible to create or observe a truly diversified market portfolio characterized in the model. In applications, people use, for example, the S&P 500 as a proxy for the truly diversified market portfolio. But because the CAPM was extremely sensitive to the market portfolio, finding the real market portfolio was important. In reality, a truly diversified portfolio, by definition, would include assets of all classes, including real assets such as gold, real estate and intangible assets. As is easy to understand, forming such a portfolio is infeasible. The proxies would never be able to reflect the return of the truly diversified market portfolio. Roll's critique is important in setting up a ground for researchers to look for further more applicable asset pricing models.

Another recent paper that questions the theoretical validity of the CAPM is Lai and Stohs (2015). The paper proved theoretically that the CAPM has serious problems of endogeneity and/or circularity. The CAPM model assumes an asset's return depends on the β. However, the beta is affected by the covariance of market return and an asset's historical return. Therefore, it was the β that is dependent on the asset's return not vice versa as the CAPM states.

Starting from the 1970s, evidence that empirical results did not support the CAPM theory began to appear. Fama and French (2004) summarized some empirical testing results on the CAPM model which centered around the intercept and the slope which is the β: Fama and French (2004) explained that the evidence from the empirical testing results is inconsistent with the CAPM using mostly the US markets (NYSE, AMEX and NASDAQ) as the market portfolio. The resulting β of the empirical testing was in fact "flatter" (an absolute value that is lower than what a model estimates) than what the CAPM determines (Black et al., 1972; Fama and MacBeth, 1973; Stambaugh, 1982). This means that even though there was a positive relationship between the β and the average returns of an individual asset, the positive coefficient of β was less than what the CAPM predicted. The returns on low β assets were too high and the returns on high β assets were too low. This flatter (an absolute value that is lower than what a model estimates) β invalidates the application of CAPM for the estimation of the cost of equity and performance analysis of managed funds. For example, when the actual β is lower in absolute value, then the β estimated by the CAPM model for a high beta stock was too high (compared with its historical returns) and for a low β stock was too low.

Apart from the lower abslute value of the β, there was also evidence that the asset or portfolio's return was not linearly correlated with the market portfolio. In other words, there were patterns in the regressions' error term that cannot be explained by the market β alone. This was reflected in the anomalies detected in the time-series regression by scholars. For example, Reinganum (1983) reported the "January effect" where the stocks' returns in January could not be explained by β. Banz (1981) reported that size was a factor that could not be explained by the asset pricing model. In 1988, Bhandari (1988) reported the leverage (Debt/Equity) loaded positively in the CAPM regression. These anomalies seriously invalidate the application of the CAPM to managed funds performance analysis. For example, a fund that held mostly low β stocks tended to produce positive abnormal returns relative to the market portfolio (caused by the "flatter" (an absolute value that is lower than what a model estimates) β). This abnormal return would result in people believing the fund manager had superb stock-picking ability, when in fact they were merely holding riskier assets.

Some other anomalous factors, such as momentum were also found inconsistent with the CAPM. For example, Bondt and Thaler (1985) reported that "buying losers and selling winners" produces positive excess returns, but Jegadeesh and Titman (1993) reported contrary findings that there were positive unexplained returns on "buying winners and selling losers" strategies. Another worth-noting anomalous factor was liquidity (trading volume) reported by Brennan and Subrahmanyam (1996) that a return premium was also associated with the level of illiquidity.

1.1.3 The Search for Extensions of the CAPM

The above problems with the CAPM led to the development of new asset pricing models, or corrections of the original CAPM. Our focus is the multi-factor models which added a few more factors into the original CAPM. Before we dive deeper into the topic of multi-factor models, we will briefly mention a few models that are alternatives to the CAPM. However, there are a vast number of attempts [2] to use models or methods that are alternatives to the original CAPM to quantify an asset's expected returns. Discussing all of them is beyond the scope of this chapter.

The first one is the arbitrage pricing model. Ross (2013) developed the arbitrage pricing theory (APT) as an alternative model to the original CAPM to try to relax the rigorous assumptions of the CAPM. The APT is similar to the CAPM, but instead of claiming that the market was the only risk factor, the APT claims that there were a few risk factors, including the market factor and

[2] Acharya and Pedersen (2005); Amihud and Mendelson (1989); Anderson and Garcia-Feijóo (2006); Ang et al. (2006); Asquith et al. (2005); Avramov et al. (2007, 2009); Baker and Wurgler (2006); Balvers and Huang (2007); Bansal and Yaron (2004); Bansal et al. (2005); Basu (1983); Bhandari (1988); Brennan et al. (2004); Brennan and Subrahmanyam (1996); Brennan et al. (1998); Campbell et al. (2008); Chan et al. (1985); Chang et al. (2013); Chen et al. (2002); Chopra et al. (1992); Chordia et al. (2001); Chordia and Shivakumar (2006); Cochrane (1991, 1996); Cohen and Frazzini (2008); Cohen et al. (2012); Conrad et al. (2013); Cooper et al. (2010); Cox et al. (1985); Cremers and Nair (2005); Da (2009); Daniel and Titman (1997); Datar et al. (1998); Dichev (1998); Dichev and Piotroski (2001); Diether et al. (2002); Dittmar (2002); Easley et al. (2002, 2010); Eberhart et al. (2004); Edmans (2011); Eiling (2013); Elton et al. (1995); Fama (1991); Fama and MacBeth (1973); Fang and Peress (2009); Ferson and Harvey (1999); Frank and Goyal (2009); Garcia and Norli (2012); Garlappi and Yan (2011); Garlappi et al. (2006); Gârleanu et al. (2012); George and Hwang (2010); Gompers and Metrick (2001); Gompers et al. (2003); Hahn and Lee (2009); Heaton and Lucas (2000); Hirshleifer and Jiang (2010); Hirshleifer et al. (2013); Holthausen and Larcker (1992); Hou and Robinson (2006); Hou and Moskowitz (2005); Huang (2009); Hvidkjaer (2008); Jacobs and Wang (2004); Jagannathan and Wang (2007, 1996); Jegadeesh (1990); Jiang et al. (2005); Jones and Lamont (2002); Kapadia (2011); Kim et al. (2012); Korniotis (2008); Kumar et al. (2008); Lehavy and Sloan (2008); Lettau and Ludvigson (2001); Li (2011); Li et al. (2006); Liu (2006); Livdan et al. (2009); Malloy et al. (2009); Ozoguz (2008); Parker and Julliard (2005); Pástor and Stambaugh (2003); Pontiff and Woodgate (2008); Sullivan et al. (2001); Teo and Woo (2004); Titman et al. (2004); Tuzel (2010); Vanden (2006); Vassalou and Xing (2004); Yogo (2006).

a firm's specific factor. However, the APT does not specify what exact factors should be included in the model, that is up to the individual user to decide.

Another two interesting alternative models are called the consumption β and intertemporal CAPM. Breeden (2005) proposed an extension to the original CAPM that uses "consumption β" instead of market β. It claims that investors' wealth, consumption and risk-aversion level affect the overall market changes. The consumption β measures how much these factors are related to the changes of the market – the original major factor that determines the risk. For example, a consumption β of 2 indicates that if the market return increases by one unit (e.g. 1%), the asset's expected return could increase by two units (e.g. 2%).

Finally, an intertemporal capital asset pricing model (ICAPM) put forward by Merton (1973) is a similar model to the CAPM, in the sense that it also tries to express the relationship between the expected return and risk of a firm. The difference is that the ICAPM regards the risk factors as time-varying as well as investor specific. The model recognizes that investors' risk appetites are specific and therefore the correct factors to be used for each investor are different. The model claims the major risk factor is still the market but recognizes time-varying macro-economic conditions.

Multi-factor models

Since the finding of the above anomalies, two streams of theoretical developments have been derived from the one-β CAPM model. One stream believes that the theory of EMH is completely outdated; the focus should be now on the irrational behavior of investors. This is also known as "behavioral finance" (Thaler, 2005, 2016). Another stream tried to add alternatives to the CAPM by introducing the APT, and believed that the market is not completely efficient, but is "self organized" to prevent arbitrage – any arbitrage opportunity will be immediately taken by investors. So extra βs can be added to capture this efficiency.

Given the one-variable nature of the CAPM and its limitations in applications, Fama and French (1993) collected a number of anomalies found previously, including size, leverage, earnings/price, book-to-market equity, and analyzed them both individually and as combinations. They reported two relatively strong anomalies that affect portfolios' returns, namely size and the book-to-market ratio. Based on this finding, they proposed a three-factor model now called the Fama-French three-factor model (FF3) that included the two factors constructed based on these two anomalies (Fama and French, 1993).

The detail of the anomalies were described as follows:

The size anomaly, which was first documented in Banz (1981). He reported that small NYSE firms earned higher returns than large firms.

The leverage (debt/equity) anomaly, which was documented in Bhandari (1988). He reported that the common stock's return was positively related to the debt/equity ratio even after controlling for market β and size.

The earnings/price anomaly, which was documented in Basu (1983). He reported that common stocks with high E/P ratios earned, on average, higher risk-adjusted returns. This result persisted even if the size effect was controlled for.

The book (equity)-to-market (equity) anomaly, which was documented in Stattman (1980) and Rosenberg et al. (1985). The latter used a strategy of buying stocks with high book-to-market and selling stocks with low book-to-market to achieve an abnormal high return. They concluded that the book-to-market was a consistent anomaly.

Based on another anomaly (also called the momentum strategy) reported by Jegadeesh and Titman (1993), Carhart (1997) added a fourth factor, the momentum factor, to the FF3 model (Fama and French, 1993) to create a four-factor model. In his paper, Carhart studied a survival bias-free sample of a total of 1892 US mutual funds' return during the period 1962 – 1993 and reported that a momentum factor explained the short-term persistence in mutual funds' returns. A momentum factor mimicked a portfolio constructed by buying last year's top decile funds and selling last year's bottom decile funds. Carhart reported that out of the total 8% return of the strategy of buying last year's winners and selling last year's losers, 4.6% was explained by the momentum factor. The practical implications of this result for investors is to avoid under-performing funds and invest in recent high-performing funds.

Finally, in 2015 Fama and French released their five-factor model (FF5) (Fama and French, 2015) which incorporated size, BE/ME, profitability and investment patterns together with market returns. Whether the FF5 model explains the stock returns better than the previous FF3 model across different countries around the globe is unknown. While in some countries the FF5 model works better (Foye, 2018), there are countries in which this model has serious problems (Foye, 2018; Kubota and Takehara, 2018).

The FF5 model is:

$$R_{i,t}-R_{F,t} = b_i(R_{M,t}-R_{T,t})+s_iSMB_t+h_iHML_t+r_iRMW_t+c_iCMA_t+e_{i,t} \quad (1.1)$$

The factors' definitions are as follows (detailed factor constructions are described in Section 2.3 of Chapter 2):

In the FF5 model, $R_{i,t}-R_{F,t}$ is the excess return on the portfolio i for period t, where $R_{F,t}$ is the risk-free interest rate. $R_{M,t}$ is the return on the value-weighted market portfolio. SMB_t (Small minus Big) is the return on a diversified portfolio of small stocks minus the return on a diversified portfolio of big stocks. HML_t

(High minus Low) is the difference between the returns on diversified portfolios of high and low B/M stocks. RMW_t (Robust minus Weak) is the difference between the returns on diversified portfolios of stocks with robust and weak profitability, where the profitability is calculated using operating profit at year $t-1$ divided by a firm's book equity at year $t-1$. CMA_t (Conservative minus Aggressive) is the difference between the returns on diversified portfolios with conservative and aggressive investment styles, where the investment style is measured using the growth of total asset at year $t-1$ divided by the total asset at year $t-2$.

1.2 Mutual Fund Performance Analysis

One of the applications of asset pricing models is analyzing the performance of mutual funds. Comparing the estimated return of the fund portfolio with its actual return will tell us whether the fund manager is able to pick a portfolio whose return is greater than what is expected, and therefore has a superb stock-picking skill. Finding a manager's skill level is important because investors are often charged high fees for such a skill. In this section, we describe some methods used in mutual fund performance analysis. Then, we compare the findings from a number of studies, which examine whether fund managers have stock-picking abilities.

1.2.1 Methods for Mutual Fund Performance Analysis

In this section, we first discuss some major methods used to analyze mutual fund performance. Then, we explore some alternative methods that enrich the methods of mutual fund performance evaluation.

Major Methods

Figure 1.2 displays the timeline for six major methods used in the evaluation of mutual fund performance. After the introduction of the CAPM, Jensen (1968) was one of the first papers which applied the theory of the CAPM to the analysis of mutual fund performance. The CAPM can estimate the expected return for a particular investment. In other words, the CAPM tells an investor what is the fair reward for taking the systematic risk that a particular investment carries. Jensen was able to compare the return of a specific mutual fund to the returns that were estimated by the CAPM model, therefore judging whether fund managers have the ability to choose stocks that generate more returns than what the CAPM indicated they should. In his paper, Jensen reported managers were not able to

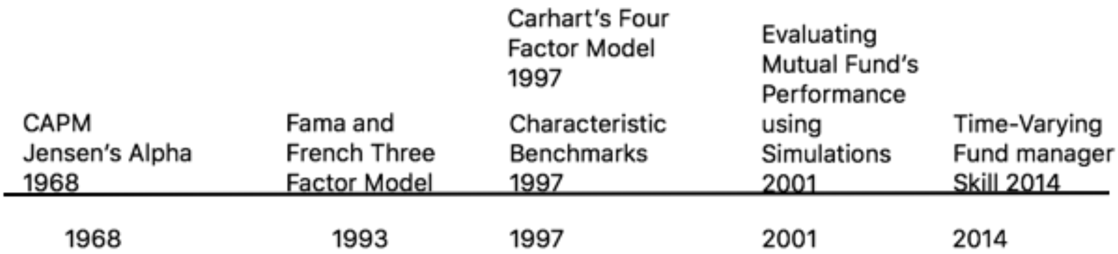


Figure 1.2: A timeline for the six major methods used in the evaluation of mutual funds performance.

pick stocks that outperform a buy and hold strategy. The finding was robust even if he ignored management expenses.

As described previously, the CAPM was under critique from quite shortly after its inception. Although the CAPM was a very popular method to measure funds' expected returns, various researchers had started to explore alternative ways to study mutual fund performance to overcome the deficiencies in the CAPM. The first improvement after the sole use of the CAPM was described in Fama and French (1993) (the Fama and French three-factor model was described in Section 1.1.3). One of the first papers that used the FF3 model was Elton et al. (1996), which used the FF3 model to estimate risk-adjusted returns when evaluating equity mutual fund performance.

Among the new factor-based methods that were developed for evaluating mutual fund performance, researchers also developed non-factor based methods. For example, Daniel et al. (1997) developed a new measurement called a "characteristic-based" benchmark to evaluate mutual fund performance. That is, instead of using the popular simple regression-based factor models, this method used a new benchmark to judge whether a fund produced an excess return. This new benchmark was made directly from matching characteristics of stocks held in the fund. One of the measurements introduced in this paper was characteristic selectivity (CS) which used as a benchmark the returns of a portfolio of stocks whose size, B/M ratio and momentum matched the stocks held in the fund. For example, for simplicity, if a fund held only IBM stock, the benchmark would be a portfolio of stock whose size, B/M and momentum matched IBM. Then the return of IBM and the return of the matching portfolio are compared. A CS score of zero says the performance of the fund can be easily reproduced by simply purchasing stocks with the same characteristics. A CS score of above zero indicated the fund manager had some stock-picking skill. Compared with the traditional regression methods, the characteristic-based method may be able to provide more accurate measures of mutual fund performance because regression-based methods often lose precision if the model is misspecified and/or if the return history is short. Their data contained 2500 stocks for the period between 1975 to 1994. The findings showed there are small excess returns generated by managers, but after considering management fees, these excess returns basically disappeared.

In the meantime, factor models were still popular methods for mutual fund evaluations. In 1997, the factor model methods were enriched by Carhart (1997) – a four factor model that added the momentum factor onto the original FF3 model (the Carhart (1997) model was also described earlier in Section 1.1.3). It was one of the major papers that rejected the hypothesis that mutual fund managers have superior stock-picking skills. In the paper, Carhart claimed that adding an extra factor – a momentum factor – to the FF3 model generated a "four-factor model" with improved explanatory power. This model explained almost all stock return variations especially the momentum anomaly which was the basis for the "hot hand effect". He explained the winning stocks possessed a momentum effect where their winning status tended to last for only one year; following the winner funds does not give an individual fund a higher return. The fact that some managers can produce persistent above-average returns was because they happened by chance to hold a large portion of these winning stocks. However, the pitfall of this method was that it could not find an explanation of why there was persistence in the worst-return mutual funds. The finding that persistence was strong among the worst-performing mutual funds was important; it proposed the question whether investors should care more about avoiding the worst-performing fund managers rather than chasing superstar fund managers, especially whether these superstar manager do exist is questionable. The dataset he used was a survival bias-free data for the period January 1962 to December 1993.

Despite the few methods accepted in the field of mutual fund evaluation, the validity of these methods was still strongly questioned by Kothari and Warner (2001). Instead of analyzing actual mutual funds whose potential out- or under-performance was unknown, Kothari and Warner (2001) simulated funds mimicking certain fund characteristics, such as size and book-to-market value, and used popular characteristic- based and regression-based fund performance measurements to evaluate those simulated funds. These measurements were comprehensive and included the CAPM, the FF3 model and the Carhart four-factor model.

During the simulation method, they randomly picked stocks from the NYSE and AMEX to form stock portfolios for the period January 1966 to December 1994, and artificially added annual excess returns of 1%, 3%, 5%, 7.5%, 10% and 15% to these portfolios. They reported after adding up to 3% annual excess returns, these methods failed to detect these excess returns. However, the study suggested event-based studies could increase test power. In the event-study, they assumed they only track the performance of mutual funds' stock purchases, and added artificial abnormal returns onto those purchased stocks. When this method was used, even a 1% abnormal return was detected 9.8% of the time compared with nearly zero for regression methods. However, the event-based study had a strong assumption that fund managers' profits were only short-lived and concentrated only in a few quarters. Therefore, further investigation was needed for this event-type of study.

The latest noteworthy method that enriched the tool box for mutual fund evaluation was in Kacperczyk et al. (2014). In this paper, the authors proposed a new definition of skill. They separated the market timing into boom and recession periods and reported that some managers had the ability to switch strategies between market expansions and recessions: they held more stocks in a market expansion and fewer stocks in a market recession. The paper therefore suggested a new managerial measurement that weighted managers' picking ability more in market boom periods. By doing so, the managers' picking ability measurements become more persistent than if we do not recognize the differences between the two types of periods. This method allows us to recognize the fact that good managers may change portfolio picking strategies during different macro-market conditions. Ferson and Schadt (1996) conducted a study based on a similar philosophy: publicly available information, such as macro-economic conditions, influence fund performance beyond what the market return can explain. In the literature, it is often interpreted as managers' timing ability. They argued that the effective use of publicly available information should not count as abnormal performance. They developed a conditional measurement that took into account the publicly available information. When they used a lagged instrument to control for publicly available information, the performance of the funds looked better: funds took less market exposure when stock returns were low and fund performance improved. This paper suggested incorporating a publicly available information variable into fund analysis for more accurate manager skill evaluation.

Other Methods

Apart from the major development in methods, there were also various methods which did not receive a lot of attention in the area of mutual fund evaluation. However, they are still worth noting.

Performance measurement without benchmarks: An examination of mutual fund returns:

Grinblatt and Titman (1993) was one of the first papers that used portfolio holdings that do not require benchmarks to analyze fund performance. The new method was based on the assumption that uninformed investors do not have any perspectives about any stocks' future returns, so their vector of expected returns was constant over time. Conversely, an informed mutual fund manager would have the right expectations about a stock's future returns, and he or she will adjust the portfolio weightings accordingly. Therefore, there will be a covariance between the portfolio weighting and the future expected return of the asset. However, this method did not become popular in the field of mutual fund evaluation, probably due to its strong assumptions and the difficulties in data collection. The authors reported that contrary to previous findings, managers do exhibit some superior stock-picking ability, especially if the funds were an aggressive growth type of fund.

Can Mutual Fund Managers Pick Stocks? Evidence from Their Trades Prior to Earnings Announcements:

Some managers were able to buy stocks that outperformed the ones they sold. Baker et al. (2010) looked at the nature of this ability and found it was around the next earning announcement that the fund managers were particularly able to buy stocks that outperformed. The paper concluded that the partial reason the managers could do this, was that they could forecast earnings-related fundamentals.

Judging fund managers by the company they keep:

The drawback of using a regression's α as a means of judging abnormal returns was that regression models can be mis-specified and, more importantly, was the short-history nature of most mutual funds. Cohen et al. (2005) tried to overcome this problem by combining Jensen's α and the extent to which the manager's holding matched the holdings of managers with distinguished records. This extent was measured by the correlation between the manager's current portfolio weights and the current weights of the benchmark managers. They did this based on the premise that managers who make similar investment decisions as high-ranked managers can also generate high expected returns. The paper reported that mutual fund returns can be predicted. In other words, there was persistence in mutual fund returns. When they controlled for Jensen's alpha, the rankings sorted by the weighted average of the extent to which the manager's holding matched those star-managers showed a great variation, which indicated that this measurement contained more information about the funds' future returns than what α alone reveals. This method brought us a step further towards overcoming the problems of regression-based methods, and it was especially useful when the number of managers in the industry was large and when the history of mutual funds was short.

Fund manager use of public information: New evidence on managerial skills:

Kacperczyk and Seru (2007) provided theoretical evidence that the more the managers rely on private information, i.e. the less they rely on public information, such as analysts' past recommendation on stocks, the better their performance. The degree to which the managers rely on public information was measured by the sensitivity of their portfolio holdings to changes in public information. The higher the sensitivity, the higher the degree of dependency on public information, and therefore the lower the manager's investment sophistication. This finding provided an additional way of judging the quality of managers. However, the data required for this study were quite extensive, including data such as trading records and profit and loss statements, and because of data paucity the sensitivity was only measured at discrete time intervals.

Mutual fund performance: An empirical decomposition into stock-picking talent, style, transactions costs, and expenses :

Wermers (2000) used mutual fund return data from January 1975 to December 1994 to decompose the excess returns of funds over the market. He reported that even though the funds outperformed the market by 1.3%, the net returns of the fund to investors were 1% short of the market. So out of the 2.3% differences, 1.6% was due to expenses and transaction costs. He showed evidence that managers have stock-picking abilities.

1.2.2 Do Managers Have Superb Stock-Picking Ability?

Although the capital asset pricing models have been evolving since shortly after the initiation of the CAPM, their applications, particularly their use in mutual fund performance evaluation, have always been lagging their developments. That is, despite the theoretical and empirical invalidation of the popular asset pricing models, these models have been used extensively by studies to evaluate mutual fund performance. Naturally, this will result in conflict among findings. In this section, we discuss some of the studies on mutual fund performance evaluation using traditional asset pricing models as well as studies using alternative methods. The studies collected here are not exhaustive, but enough to demonstrate that there are serious contradictions in the findings of mutual fund performance, and therefore further methods are needed to enrich the area of mutual fund performance evaluation.

Table 1.1 shows the three groups of findings that are rather contradictory. For the study period 1968 to 2017, there are a large number of studies reported which showed that, yes, managers do have stock-picking abilities, although most of them used a non-asset pricing model approach. For example, Baker et al. (2010) reported that fund managers do have stock-picking ability. One reason that mutual fund managers could generate excess returns was that they could forecast earnings- related fundamentals. Ferson and Schadt (1996) argued that incorporating a publicly available information variable into fund analysis results in more accurate manager skill evaluation and concluded that, yes, managers can generate excess returns.

There are also studies that do find small excess returns on mutual funds; however, these excess returns disappear after considering the costs. For example, Daniel et al. (1997) used a dataset containing 2500 stocks for the period between 1975 to 1994 and reported there were small excess returns generated by managers but after considering management fees, these excess returns basically disappeared. Wermers (2000) reported that even though the funds outperformed the market, most of it went to expenses and transaction costs.

Finally, there are papers that reported mutual funds cannot beat the market. For example, Jensen (1968) was one of the first papers that applied the theory of the CAPM to the analysis of mutual fund performance. He was the first to report that managers were not able to pick stocks that outperform a buy and hold strategy.

Therefore, a better model is still in demand despite the variety of models that are available for researchers to use. In a later chapter, we will try to discover a more sensible factor model by redefining the size and book-to-market ratio and reconstruct factors.

	Major findings
Panel A:	**Studies that confirmed managers stock-picking skill**
Ippolito (1989)	Mutual funds, net of all fees and expenses, outperformed index funds after adjusting for risk, for the study period 1965 to 1984.
Grinblatt and Titman (1993)	Managers did exhibit some superior stock-picking ability especially if the funds were an aggressive growth type of funds.
Elton et al. (1996)	Managers have stock-picking ability.
Ferson and Schadt (1996)	After controlling for public information, fund performance improved indicating managers' stock-picking ability.
Wermers (2000)	There were evidence that managers have stock-picking abilities.
Cohen et al. (2005)	The paper reported that mutual fund returns can be predicted. In other words, there was persistence in mutual fund returns.
Kacperczyk and Seru (2007)	The more the managers rely on private information, the better their performance.
Kacperczyk et al. (2008)	Yes, there were persistent excess returns in unobserved actions that indicate managers' stock-picking ability.
Baker et al. (2010)	It was around the next earning announcement that the fund managers were particularly able to buy stocks that outperformed.

Kacperczyk et al. (2014)	Some managers had the ability to switch strategies between market expansions and recessions: they held more stocks in a market expansion and less stocks in a market recession.
Panel B:	**Studies that confirmed skill, but the fees eliminated the excess returns**
Daniel et al. (1997)	There were small excess returns generated by managers but after considering management fees, these excess returns basically disappeared.
Wagner and Margaritis (2017)	Mutual funds at an aggregate level have higher returns compared to benchmarks indices, although they disappear after deducting costs.
Panel C	**Studies that rejected managers stock-picking skill**
Jensen (1968)	Managers were not able to pick stocks that outperform a buy the market and hold strategy.
Malkiel (1995)	Funds in aggregate under-perform benchmark portfolios.
Carhart (1997)	A momentum factor explained the “hot hand” effect.

Table 1.1: A list of studies which confirmed or rejected the question of whether mutual fund managers have stock-picking ability.

1.3 Factor Models and Performance of Mutual Funds in Emerging Markets

1.3.1 The Factors That Explain Stock Return Variation in non-US Developed Markets

Before we go into the central topic – factors that explain the stock return variations in the emerging markets – we first briefly look at how well factor models work in some of the non-US developed market.

Interestingly, even though a number of studies have focused on the US market, the literature on the non-US developed market is substantially less. Our discussion focuses on the three factors within the context of the Fama and French three factor model because the number of studies focus on the Fama and French five factor models is even less owing to the fact that the five factor model was only recently published (2015).

Firstly, instead of studying individual countries, Fama and French (2012) documented a comparison study on how well the three factor model explained regional markets, including North America, Europe, Japan and Asia Pacific. They could not find a size premium in any of these regions but a strong value effect in them. Also, the value effect decreases as the size increases, except for Japan. The study implied the use of Fama and French three factor model should be customized for local market condition rather than international or aggregated market conditions.

There are also papers investigating Fama and French three factor model in individual non-US countries. Malin and Veeraraghavan (2004) investigated France, UK, and German stock markets and report that size effects are presented in France and Germany, and there is a reversal size effect in the UK. As for the value effect, the study reported there are reversal of the value effect in all of these countries. Kilsgård and Wittorf (2010) investigated the Sweden stock market and confirmed that the Fama and French three factor model added more explanatory power to the original CAPM. Kubota and Takehara (2018) studied the Japanese stock market and report, similar to Fama and French (2012), there was a strong value effect, and non-significant size effect in this market. The size effect, interestingly, became strong when they removed the value factor from the Fama and French five factor model.

1.3.2 The Factors That Explain Stock Return Variation in Emerging Markets

Apart from the developed US market, stock return variations and factors explaining the variations are also studied in emerging markets. Studies at an aggregate level claimed that the value factor of the FF3 model and the momentum factor explain emerging market returns well (Cakici et al., 2013).

At an individual level, stock return patterns were also studied. For example, Rogers and Securato (2007) reported a two-factor model containing only the market and the size factor explained the Brazilian stock market returns well. Basiewicz and Auret (2010) reported that the South Africa stock market (JSE) has both the size effect and the value effect. Mehta and Chander (2010) also reported both the size effect and the value effect in the Indian market. Czapkiewicz and Wójtowicz (2014) examined a four-factor model in the Warsaw Stock Exchange (WSE) and reported that the four-factor model does explain the stock return variations in this market.

1.3.3 The Mutual Fund Performance in Emerging Markets

Compared with the more developed US market, emerging markets have common characteristics, such as weakness of legal institutions and underdeveloped capital markets. Despite these common traits, studies still reported contradictory results on mutual fund performance. For example, Mehta and Chander (2010) reported mutual funds in emerging markets have a large spread between winner and loser funds, and those winner funds have substantial large excess returns which are large enough to cover costs. Wagner and Margaritis (2017), however, reported mutual funds in emerging markets (except China, whose funds have large excess returns) have small excess returns, but they disappeared after considering costs. More surprisingly, Basu and Huang-Jones (2015) reported that diversified emerging market funds do not outperform the market benchmark index.

Laes and da Silva (2014) studied the performance of mutual fund returns in Brazil for the period 2002 to 2012. They used the Carhart's four-factor model as a benchmark, and reported that the best-performing mutual funds were mostly due to luck and worst-performing funds were due to bad managements. Białkowski and Otten (2011) examined the performance of mutual funds in the Polish market. They reported that on average funds are not able to add value. However, domestic funds outperformed international funds. Also, contrary to the findings in the developed markets, the Polish mutual funds had strong persistence for up to one year, and the winning funds were able to significantly beat the market.

1.4 Factors Explaining Stock Returns and Mutual Fund Performance in China

1.4.1 Stock Return Variation in China

China has an emerging economy. Although its capital market is large (ranked second after the US market as of January 2018), the market is still young and less effectively regulated than developed markets. There are a smaller number of studies on anomalies that help to explain the stock return variations in China and those studies were also contradictory.

As shown in Table 1.2, the findings on what factors affect the Chinese market among the size and the value factor can be separated into three groups.

The first group of studies claim that there are strong positive size and value effects in China. For example, Lin et al. (2012) studied 237 individual stocks on the Shanghai Stock Exchange for the period January 2000 to December 2009 and reported that the three risk factors in the FF3 model were good proxies for explaining the portfolio return variations. Zhang and Xu (2014) studied all Chinese listed companies between 1992 and 2012 and also reported that the FF3 model was a good model to explain the Chinese stock return variations, although they suggested using a market portfolio containing only tradable shares and using book-to-price ratio instead of book-to-market ratio. They claimed that the reason for using a book-to-price ratio instead of a book-to-market ratio is because there were few segmented markets in China (Shanghai Stock Exchange, Shenzhen Stock Exchange and the Hong Kong Stock Exchange) and a market value of a share in one segmented market may not be the same as in another segmented market. Therefore, using a book-to-price ratio captures stock fundamentals better, where the price is the price of a stock at the end of the previous year. Three earlier studies that reported similar findings about the size and value effect are Wong et al. (2006), Wang and Di Iorio (2007) and Chen et al. (2007). Wong et al. (2006) reported that smaller stocks and value stocks performed better in the period 1993 to 2002. The size and value effect, however, became insignificant in a down market. Wang and Di Iorio (2007) studied stock returns in China in 1994 to 2002 and reported a strong size effect and value effect. The study claimed the market β alone lacked explanatory power and was inconsistent in an up and down market. Chen et al. (2007) studied stocks from both the Shanghai Stock Exchange and the Shenzhen Stock Exchange between 1998 and 2001 and reported there were both size and value effects.

The second group of studies in Table 1.2 claimed a positive size effect and a negative value effect (Guo and Wang, 2014; Drew et al., 2003; Zhan Hui, 2004). Guo and Wang (2014) studied the top 100 largest stocks' returns during 2004 to 2013 and reported the FF3 model was more powerful than the CAPM. Most surprisingly, they detected a "reversal" value effect, which means the intercepts of regressions increases as the BE/ME decreases, and this is true for portfolios in every size group. The "reversal" value effect, however, could be driven by the small sample size (100). Drew et al. (2003) reported that small and low book-to-market equity firms in addition to the market portfolio generate superior risk-adjusted returns.

The final group of studies claimed similar results on the size effect (positive size effect) but inconsistent or no effect of the book-to-market ratio (Wang and Xu, 2004; Qi, 2018). Wang and Xu (2004) studied stock returns from 1996 to 2002 and reported that size but not book-to-market ratio helped explain the cross-sectional difference in the Chinese stock market. Qi (2018) studied the FF5 model and concluded that the two extra factors – the profitability and investment – added no explanatory power to the original FF3 model. Not only that, the

Study	Size effect	B/M effect
Zhan Hui (2004)	+	+
Wong et al. (2006)	+	+
Wang and Di Iorio (2007)	+	+
Chen et al. (2007)	+	+
Lin et al. (2012)	+	+
Zhang and Xu (2014)	+	+
Drew et al. (2003)	+	-
Guo and Wang (2014)	+	-
Qi (2018)	+	No effect
Wang and Xu (2004)	+	No effect

Table 1.2: The size and value effect in China.

value factor was also not significant in the Chinese market. Therefore, a two-factor model containing the market and a size factor was the model to explain the Chinese stock market return variations.

1.4.2 The Mutual Fund Performance in China

As shown in Table 1.3, mutual fund performance has also been studied in China. Even though there are only a small number of studies available, the contradictions in findings are obvious. Chen (2013) and Chi (2015) confirmed that the Chinese mutual fund managers have stock-picking ability. Yet, Su et al. (2012) reported mutual funds may underperform or outperform the market in different macro-economic conditions. Similarly, Kiymaz (2015) reported initially there was excess risk-adjusted returns in mutual fund supported by the positive αs[3] in the whole study period of 2000 to 2013, but when the whole period was split into sub-periods, the excess performance became inconsistent.

[3] If a model fully captures the stock return variations, then the regression of the factors in the model on stock returns would have a zero intercept, also known as the α. If the regression produces a statistically significant positive α, then we would claim that the stocks generated a higher risk-adjusted return than what the model estimated it to produce.

Study	Out-performance	Findings
Su et al. (2012)	inconsistent	Funds under-perform and out perform the market under different macro market conditions.
Chen (2013)	yes	Chinese mutual funds out perform the markets.
Kiymaz (2015)	inconsistent	Chinese fund do not consistently provide excess returns and show great variation.
Chi (2015)	yes	Managers' stock-picking skill helps explain a substantial amount of their out performance

Table 1.3: Mutual fund performance in China. The "Yes" indicates the study concluded that managers do have stock-picking ability. The "inconsistent" indicates that the study concluded that managers' stock-picking ability were inconsistent.

1.5 Introduction to the Chinese Mutual Funds Industry

1.5.1 An Overview of the Stock Market in China

History of the Chinese stock markets

The Chinese financial market has always been composed of "parallel markets" since its initiation in the mid-nineteenth century. That is, it consists of two streams or markets of different geographically located investors that operate in different segments of the market in China. One stream which was dominated by foreign investors and their businesses was the result of the Chinese loss of the "Opium War" (1860), and it was forced to open the five treaty ports in the cities of Shanghai, Guangzhou, Fuzhou, Xiamen and Ningbo. For those foreign investors, capital was raised in foreign cities, such as London, or in English colonies, such as Hong Kong or India. In 1869, the first set of Chinese shares was issued within China by a British company. This was followed by a number of other foreign companies monopolizing in sales of tobacco, banking services and other commodities. As the number of domestically issued shares increased, the Shanghai Share Broker Association, the previous form of the Shanghai Stock Exchange, was established in 1891. In 1895, at the end of first Sino-Japanese War, foreign business activities aggressively expanded after the eight-nation alliance (an international army composed of soldiers from Japan, Russia, the British Empire, France, the United States, Germany, Italy, Austria-Hungary) occupied Beijing and forced the Qing Imperial government to allow foreign companies to extend their business throughout China under the protection of the unequal Sino-foreign treaties (Ji and Thomas, 2003). As the foreign businesses in China boomed, the Shanghai Stock Exchange was restructured in 1903, and was also registered in Hong Kong as a members-only stock exchange where only registered members could trade. The Hong Kong exchange had 100 members of which 87 were Western companies and 13 were Chinese companies.

The other stream, which consisted of Chinese domestic businesses, started in 1872 when the Chinese government's major advocate of Western industrialization, Li Hong Zhang, appointed the Zhu brothers to establish the Shanghai China Merchants Steamship Navigation Company. It was the first Western style Chinese company that issued Western-style stocks. After that, a number of similarly styled companies were established, and their issue of shares included insurance, coal, fabric and telegram companies. In September 1882, the first Chinese-owned stock broker, the Pingzhun Stock Trading Company, was established (Morck, 2007). However, in the following year, due to a combination of different causes, including excessive speculation and business credit default, China experienced the first domestic stock market crash which lasted more than 10 years. In 1904, Liang Qi Chao (a well-known Chinese journalist and legendary reformist) advocated the reestablishment of a formal stock trading exchange which led to the establishment of the first well-organized stock exchange and the promulgation of the first security exchange regulations in around 1914 just before the First World War. The Chinese domestic stock market started to boom again, and as a result the Beijing Securities Trading Exchange was established in 1918 in the capital Beijing. Within two years, the Shanghai Stock Exchange was also re-established and its operation expanded. The Shanghai Stock Exchange became the largest stock exchange in Far East Asia by 1934 when the famous Shanghai Security Building was built. During the period between 1939 and 1949, the Shanghai stock exchange experienced a series of close-downs and re-openings due to the second Sino-Japanese war, the Pacific War and the Civil War. In 1949, following the establishment of the People's Republic of China, it was finally closed down by the Communist Party. This was reopened after 41 years in December 1990.

After the closing-down of the Shanghai Stock Exchange, the Chinese Communist Party opened the Tianjin Stock Exchange - the first stock exchange established by the Communist Party in 1949 and the Beijing Stock Exchange in February 1950. However, the stock exchanges did not attract enough businesses and both were closed in 1952. In 1953, due to the adaptation of Soviet Russian central planning methods of capitalization and the Cultural Revolution,[4] China closed its markets to the rest of the world. Soon after, the government declined any type of business credit and later cancelled the national credit system. For the period 1968 to 1978, mainland China did not have any financial or credit system; in fact commercial activities were banned and no bonds or stocks existed in that period. Therefore, for about 30 years, during the period between the establishment of the People's Republic of China in 1949 and 1978 (two years after the death of Chairman Mao), through a series of anti-capitalist campaigns, China had reached a complete zero-government bond and zero-business credit status.

In 1978, Deng Xiaoping emerged as the dominant figure in China's leadership and began a period of opening-up of the Chinese markets to the rest of the world. China officially started the process of market opening-up where individuals were allowed to trade. For example: peasants began to have more rights in managing their lands; in 1978, for the first time, there was a commercial deal between the Chinese government and an aerospace company, Boeing, to buy a number of their aircraft. Following that, the Coca-Cola Company announced their intention to open a production plant in China.

Since the early 1980s, the issuing of treasury bonds and trading of company stocks and corporate bonds were gradually resumed. In December 1990, the

[4] The Culture Revolution was a national campaign initiated by the Chinese government led by Chairman Mao, aimed at establishing communist ideology through purging the remnant of traditional values and capitalism. It started in 1966 and ended in 1976, and therefore was also called the "10-year turmoil".

Shanghai Stock Exchange was re-established and the Shenzhen Stock Exchange was established in July 1991.

The development of the Chinese domestic stock market

In China, the equity market consists of a main board (including small- to medium- sized enterprise boards), Growth Enterprise board (contains smaller companies with some growth potential) and National Equity Exchange and Quotations (an over-the-counter system for trading shares of public listed companies that are not listed in the other two boards).

In terms of availability to different investors, there are three types of shares: A shares, which are denominated in RenMinBi (RMB); B shares, which are in US dollars if listed on Shanghai Stock Exchange and Hong Kong dollars if listed on Shenzhen[5] Stock Exchange; and H shares which are mainland Chinese companies who are listed on Hong Kong Stock Exchange.

It is worth noting that the Chinese government adopted the International Financial Reporting Standard (IFRS) in 2006. Also, as the Chinese market developed and matured, the MSCI Emerging Market Index, for the first time in 2018, included 5% of Chinese. This forces passive funds to invest in the Chinese stocks. Despite this, there is an intention to increase the weight of the Chinese stocks in the index.

On the main board, the number of companies has grown from 53 in 1992 to 2613 by the end of 2014, see Figure (1.3). Within it, the number of stocks listed on the small-sized enterprise board had reached 732 by the end of 2014. The number of stocks in the medium-sized enterprise board had reached 406 in the same period.

The total market capitalization on two stock exchanges as of December 2014 amounted to $US 6,004.9 billion with the Shanghai Stock Exchange accounting

[5] In Chinese, Shen Zhen is two - words, but usually written as Shenzhen in English.

for $US 3932.5 billion and the Shenzhen Stock Exchange accounting for $US 2072.4 billion (Table 1.4 and 1.5), ranking second globally following the U.S. The total capitalization of the two stock exchanges was equivalent to 58.53% of its GDP (see Figure 1.4), which indicates that the Chinese stock market is still an emerging capital market[6].

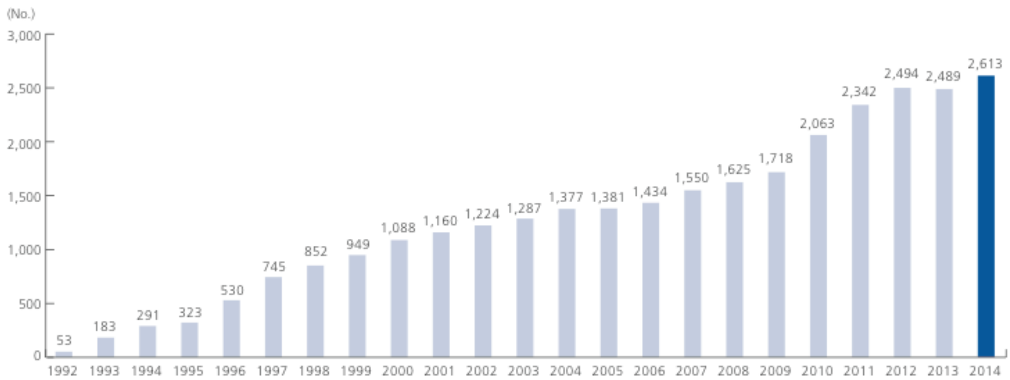


Figure 1.3: The number of Chinese listed companies in both the Shanghai Stock Exchange and the Shenzhen Stock Exchange. Data source: China Securities Regulatory Commission (CSRC).

Characteristics of the Modern Chinese Market The characteristics which make the Chinese market different from the rest of the markets in the world:

- The development of the financial market is very much in line with changes in the political environment. In other words, the way the market functions are carried out reflects the stage of China's political reforms. It is well known that the functioning of the stock market in China has been perceived as operating under a very different set of rules from typical Western-style financial markets in terms of policy-making and political influences. For

[6]Emerging markets typically have lower per-capita incomes, above-average socio-political instability, higher unemployment, and lower levels of business or industrial activity relative to the United States. They also typically have much higher economic growth rates as well as higher risks.

Stock Exchange		
Rank	Name	Market Capitalization (in Billion USD)
1	NYSE Euronext (US)	19351.4
2	NASDAQ QMX	6979.2
3	Tokyo Stock Exchange	4378.0
4	London Stock Exchange	4012.9
5	Shanghai Stock Exchange	3932.5
6	NYSE Euronext (Europe)	3319.1
7	HKSX	3233.0
8	Toronto Stock Exchange	2093.7
9	Shenzhen Stock Exchange	2072.4
10	Frankfurt Stock Exchange	1738.5

Table 1.4: The rank of capitalization by stock exchange. Data source: World Federation of Exchanges

Country or Jurisdiction			
Rank	Name	Region	Market Capitalization (in Billion USD)
1	USA	North America	26330.6
2	China	Asia	6004.9
3	Japan	Asia	4378.0
4	UK	Europe	4012.9
5	France	Europe	3319.1
6	Hong Kong	Asia	3233.0
7	Canada	North America	2093.7
8	Germany	Europe	1738.5
9	India	Asia	1558.3
10	Switzerland	Europe	1495.3

Table 1.5: The rank of capitalization by country and region. Data source: World Federation of Exchanges

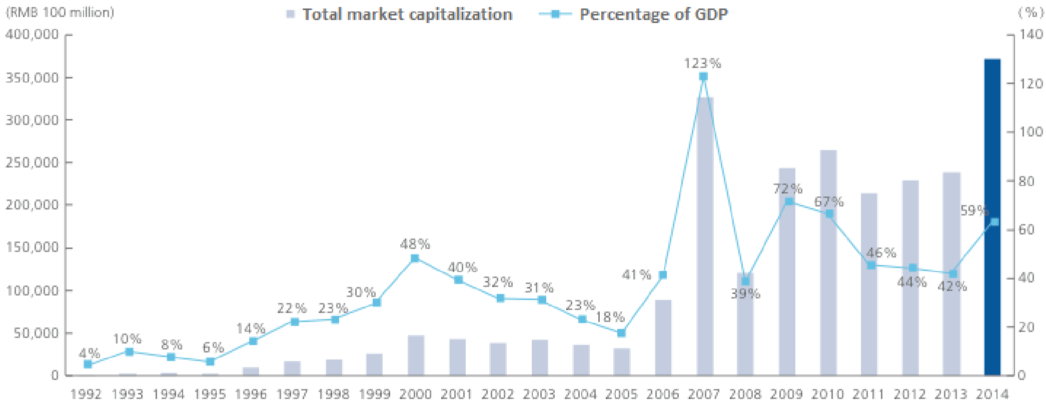


Figure 1.4: Total Chinese market capitalization of the Shanghai Stock Exchange and the Shenzhen Stock Exchange and as a percentage of GDP for the year 1992 to 2014. Data source: China Securities Regulatory Commission (CSRC).

example, the market is seen as heavily politically controlled for supporting state-owned enterprises and promoting fast market growth (Heilmann, 2002). Another example is the politically connected initial public offering (IPO) described in Fan et al. (2007). However, it is ambiguous how the roles of the politically-driven market mechanism have changed in this transitional economy. On one side, for the Chinese society to transform from one extreme form (Marxism) to another extreme form (free market), the character in the original form has to be in existence or, in other words reduced gradually, to guide or stabilize the whole system through the transitional period.

- The shares are separated into different classes: Class A, B and H. A shares are available to Chinese domestic investors; B shares are available to foreigners; and H shares are the shares listed on the Hong Kong Stock Exchange (HKSE).

- There is a lack of company transparency (Ang and Ma, 1999; Lin and Swanson, 2008), a lack of modern accounting standards, a still developing financial institution infrastructure and a pattern of scandal and market manipulations that have hurt investors' trust in the functioning of stock markets (Ji and Thomas, 2003).

1.5.2 Review of Mutual Fund Industry

Growth in size and performance

The mutual fund industry of China was established in 1998. In 17 years, its size has grown from $US 13 million in 1998 to $US 708,884 million in quarter one of 2015. The number of open-ended mutual funds has grown from 5 in 1998 to 1763 by the end of 2014.

Figure 1.5 shows the historical returns of equity mutual funds, the Shanghai Stock Exchange Composite Index (SSE) and the China Security Index 300 (CSI300) from 2003 to March 2013. Equity mutual funds provided the highest returns in six out of the 11 periods (2003, 2004, 2005, 2008, 2010 and 2013). Out of the five periods that both the SSE and the CSI300 provided negative returns, equity funds provided the highest returns in four periods, which indicates market down turns and shows equity funds are a better investment option than market indices.

1.5.3 A Comparison of Mutual Funds Industries among USA and BRICS Countries

In the last decade, the mutual fund industry has grown dramatically. The total assets under management[7] of the Chinese mutual funds industry increased from $0.5 trillion RMB in 2004 to $4 trillion RMB in 2013 (Asset Management Association of China). The number of security investment companies grew from two

[7]Total assets under management include both mutual funds and segregated accounts of non-public-offering assets.

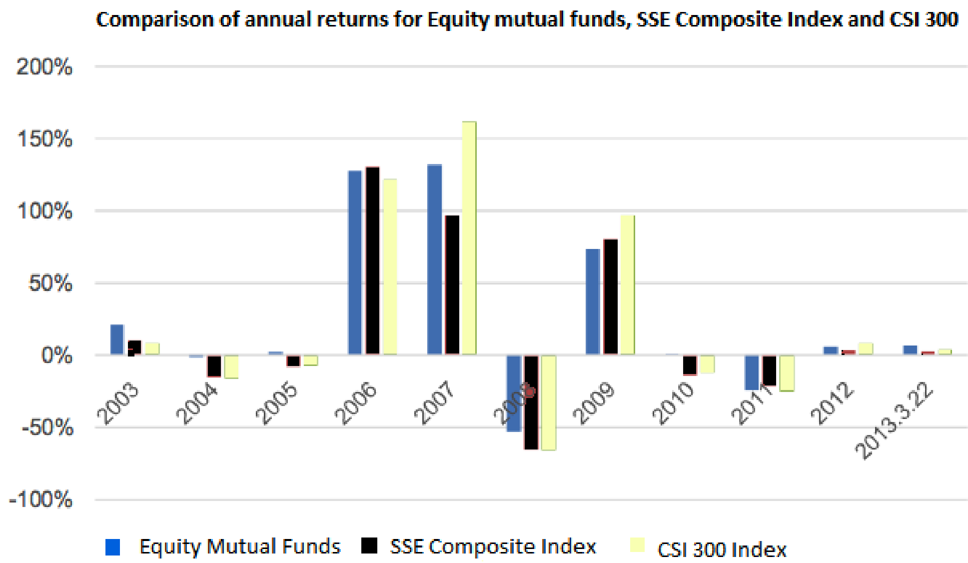


Figure 1.5: The comparison of historical annual returns of equity mutual funds, SSE composite Index and China Security Index 3000. Data source: China Galaxy Securities research center.

in 1998 to 89 in 2013 (China Securities Regulatory Commission). Chinese security law has been developed tremendously since China entered the World Trade Organization (WTO) in 2001. The Chinese government also gradually opened the domestic market to foreign investors and companies via programs such as the Qualified Domestic Institutional Investor (QDII) and the Hong Kong-China Mutual Fund recognition scheme. Mutual fund industries in developed and most other emerging countries have been studied rather thoroughly; the Chinese mutual funds market has not been studied in depth given its short history and differences in political structure. In this section, we compare the mutual funds industries of US and BRICS countries (Brazil, Russia, India, China and South Africa). We choose the US market because it represents a Western, developed financial market. The reason we also compare the Chinese mutual funds market to the other BRICS countries is because the five countries are at a similar developing stage (Prokurat and Fabisiak, 2012).

In the studies that concentrate on the more developed mutual funds industries, several aspects have been studied frequently. For example, Otten and Schweitzer (2002) compared the structure, characteristics and conduct of the mutual funds industries in European countries and the US.

Therefore, in this section, we examine the characteristics of six countries, namely the USA, Brazil, Russia, India, China and South Africa by comparing their

1. *Mutual fund industry structures*
2. *Growth in asset sizes for equity funds*
3. *Equity mutual funds as a percentage of total mutual fund value*
4. *Concentration ratios*
5. *Management fees*
6. *Distribution channels*

We will then take the approach of Otten and Schweitzer (2002), the structure-conduct-performance (SCP) paradigm to test the hypothesis of whether the Chinese mutual fund industry has the same characteristics as the US and the other BRICS countries.

The Structure of the Mutual Fund Industry in the US and BRICS countries

The US mutual fund market was the largest in the world as of December 2014; the total market capitalization of its mutual fund industry was $15.8 trillion and accounted for 51% of the world total mutual fund capitalization (statista, 2019).

Table 1.6 shows data for the total net assets, number of funds and average size of the mutual fund market in each of the six countries as at the end of 2014 collected from the Bloomberg database[8]. The data confirms that, indeed, the US has the largest mutual fund industry in the world, followed by Brazil (out of the BRICS countries). The smallest mutual fund industry among these countries is Russia, which coincides with Russia's conservative policy towards the mutual fund market. In terms of funds' average size, the US has by far the largest size followed by China, indicating there are not as many small funds in China as in other emerging markets, for example, Brazil.

Characteristics of Major mutual fund markets (in million US$)			
	Assets Under Management	Number of Funds	Average Size
United States	15,852,341	7923	2001
Brazil	989,542	8560	116
Russia	1704	392	4
India	134,630	723	186
China	708,884	1763	402
South Africa	146,474	1171	125

Table 1.6: The characteristics of the major Asian mutual fund market and the United States as at the end of 2014. Source: Investment Company Institute (ICI) Quarter 4 2014 world market summary. For Russia, the data was collected from www.investfund.ru. Note data are rounded to the nearest integer.

Table 1.7 shows the asset allocation of the mutual funds industry. It is clear that 74% of US mutual fund market were equity and bond, where equity funds accounted for 52% of the total domestic mutual fund market. For Brazil, only 7% of the funds were equities and 58% of the market consisted of bond funds. For China, money market and equity were the two largest portions of the mutual funds market. The money market accounts for 47% percent of the total domestic mutual funds market, which is the largest portion among the six countries. For South Africa, the type of fund that takes the largest percentage is balanced or mixed. It is also the largest among the six countries.

Figure 1.6 shows the growth of assets sizes for equity funds from 2007 to 2014

[8]The Bloomberg is a large private vendor of financial data.

	Asset allocation (in %)				
	Equity	Bond	Money Market	Balanced or Mixed	Other
United States	52	22	17	9	<1
Brazil	7	58	5	20	11
Russia	35	37	3	13	12
India	32	39	21	3	5
China	30	8	47	14	1
South Africa	24	4	14	49	9

Table 1.7: Asset allocation of mutual funds industries in USA and BRICS countries as of Quarter 4 2014. Source: Bloomberg

setting year 2007 to 100 as an index. It is clear that the equity portion had experienced a big drop in 2008 for all countries, the biggest drop was Russia at nearly 80%. All of them bounced back in 2009 but mostly below their base level in 2007; only Brazil's rose above the base level to near 120% in 2009. Russia has stayed below the base level since the big drop in 2008 (Russia's stock market data are not available from 2011).

Table 1.8 shows the equity funds as a percentage of total mutual fund market value for the years 2008 to 2014. It gives some insight into the development of the demand from individual investors for equity mutual funds. The US has by far the largest equity portion of their domestic market in all periods. Brazil's equity portion of their mutual fund market was the second largest among the six countries in the whole study period; it reached its highest level at 9% in 2014. China, India and South Africa have similarly low equity mutual funds to total market ratios, which indicates that equity mutual funds still have good potential to develop.

The supply of the fund products by investment companies is important. Large fund management companies usually manage a number of funds with different investment styles or purposes. It makes it easier for investors to switch funds

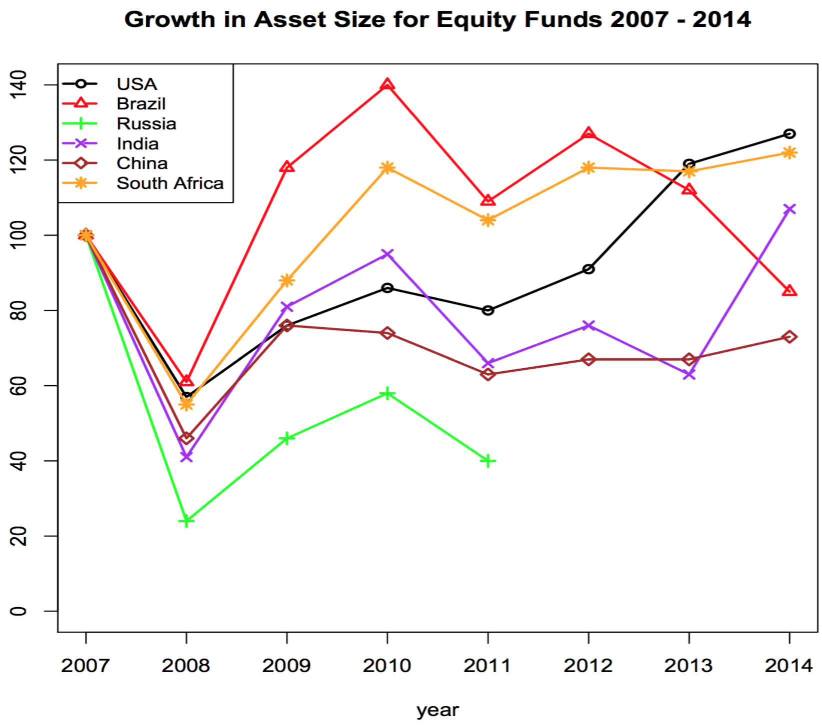


Figure 1.6: The growth of the market capitalization of Equity Funds for US and BRICS countries for the year 2007 to 2014 using 2007 as a base. Data source: World Bank.

Equity Mutual Funds as a Percentage of Total Equity Market Value							
	2008	2009	2010	2011	2012	2013	2014
United States	32%	33%	33%	33%	32%	32%	32%
Brazil	8%	8%	7%	7%	8%	9%	8%
Russia	<1%	<1%	<1%	<1%	<1%	–	–
India	3%	3%	2%	3%	2%	2%	3%
China	5%	4%	4%	5%	5%	5%	3%
South Africa	3%	4%	5%	6%	5%	4%	4%

Table 1.8: Equity Mutual Funds as a percentage of total market value of all domestic shares for USA and BRICS countries for the year 2008 to 2014. Source: ICI world market summary, ICI quarterly mutual fund summary, CSRC yearly statistics. The figures for Russia for the years 2013 to 2014 were not available on the ICI website.

within the same investment fund companies. The size of assets under management by top fund companies also indicates the level of competition in the fund markets. High concentration ratios (the percentage of the top funds to total mutual funds) indicate a high level of oligopolistic and therefore a low level of competition in the market. In other words, only a few big investment companies are controlling the market.

Table 1.9 presents the concentration ratio of the six countries. The percentage is highest for India. The US is 43%, which is the second highest. China is 28%, which is quite low among the three countries that have data available. This indicates that the Chinese market is relatively new, and there are no monopoly investment companies yet (compare with the Indian and the US markets in this section).

Concentration Ratio	
United States	43%
Brazil	N/A
Russia	N/A
India	56%
China	28%
South Africa	N/A

Table 1.9: Concentration ratio calculated as the sum of the market value of the largest five fund management companies as percentages of total fund market capitalization. Data Source: for USA: ICI 2015 factbook data, December 2014. For China: 2015 Statistic Asset Management Association of China (AMAC), December 2014. For India: www.mutualfundindia.com, June 2015.

1.5.4 Summary and Research Questions

After the creation of the CAPM, it did not take long for scholars to bring forward a plethora of critiques and attempts to find alternative models with improved explanatory power.

Surprisingly, despite the critiques of the CAPM, for a long time people used it for equity mutual fund performance evaluations. Such evaluations are based on the idea that if the return of an asset can be estimated by an asset pricing model, then the return of the portfolio (also an asset) held by a mutual fund manager can be compared with it. A good fund manager will tend to hold portfolios whose returns are higher than what a capital asset pricing model estimates.

Although various studies started to realize the inefficiency of the CAPM and started to use alternative models and methods to evaluate mutual fund performances, the methods used in mutual fund performance analysis always lagged the development of asset pricing models.

While the development of asset pricing models and their use in mutual fund performance evaluations were hotly discussed in the developed US market, researchers also looked at their use in the emerging markets.

The most interesting market among emerging countries is the Chinese stock market given its unique structure, growth and characteristics.

A number of attempts tried to address the two important questions: 1) What combination of factors in the FF5 model best explains the variations in the stock returns in the Chinese market? 2) Do the Chinese mutual funds out-perform or under-perform after risk adjustment?

After researching the answers to the above questions in the literature, one fact became certain – they are still not answered! As for the first question, although people tried to answer it by using different combinations of factors, it was never clear whether redefining the factors would affect a model's explanatory power. That is, if the definition of a small stock is a stock smaller than the 50th percentile of all stocks in the Chinese stock market, then does defining small stocks as 40th percentile, 30th percentile, 20th percentile, 10th percentile, or 5th percentile make any difference to the model's explanatory power? This research question is important given the fact that big listed firms in China were normally previously state-owned firms, while small firms were normally established from purely private funds. Therefore, it was uncertain exactly what breakpoint defined "small" and "big" appropriately in the Chinese stock market.

Once the first question is dealt with, we naturally come to the second question: Can the model containing newly defined factors consistently evaluate mutual fund performance in China?

Therefore, in the following three chapters, we will answer these two questions. In Chapter 2, we will examine the three- and five- factor models and compare their explanatory powers. Then in Chapter 3, we will carry on with a sensitivity analysis where we test whether redefining factors, such as the size factor, can improve the model's explanatory power. For example, we will test whether redefining size as the 5th, 10th, 20th, 30th and 40th percentile of all stocks in the market make any difference to the model's explanatory power. Then, in Chapter 4, we will use the best model we find in Chapters 2 and 3 to evaluate the Chinese mutual fund performance and investigate if the model produces consistent outcomes. Chapter 5 concludes.

Research question 1:

What combination of factors in the Fama and French five-factor model best explain the variations in the stock returns in the Chinese market?

Research question 2:

Does redefining the factors affect a model's explanatory power? That is, if the definition of a small stock is a stock smaller than the 50th percentile of all stocks in the Chinese stock market, then does defining a small stock as the 40th percentile, 30th percentile, 20 percentile, 10th percentile, or 5th percentile makes any difference to the model's explanatory power?

Research question 3:

Can the newly defined factor model help explain the performance of the Chinese mutual funds?

2. Fama and French Five Factor Asset Pricing Model: An Application in the Chinese Stock Markets

As discussed in the previous chapter, recent theoretical work on asset pricing models has evolved from a single one-factor model (CAPM) to multiple-factor models for improved explanatory powers on stock return variations. These works include the three-factor model of Fama and French (FF3), the four-factor model of Carhart, and most recently, the five-factor model of Fama and French (FF5). These models are actively examined in markets around the world and are applied especially in the area of mutual fund performance analysis.

While these factor-style models are flourishing in markets around the world, they have received only a little attention in the Chinese stock markets and there are only a few papers that have studied and applied these models. More importantly, these limited papers seem to produce inconsistent findings. For example, Zhan Hui (2004) finds positive β on the HML factor, Drew et al. (2003) finds a negative β on the HML factor and, more interestingly, Qi (2018) find that the HML is not even a factor in the Chinese stock market. The inconsistency seems to focus on only the HML factor. We suspect there are two reasons for such inconsistency. Firstly, the HML could be a weak factor, if it is a factor at all; secondly, the short history of the Chinese stock market makes it hard for the linear regressions to pick up patterns on the factors consistently. It is reasonable to have at least 10 years worth of monthly returns to run reliable regressions, yet the Chinese stock market only started in 1991 with only two companies.

Hence, to investigate properly the factors in the Chinese stock markets, we set up the chapters of this thesis as follows: chapter 2 investigates how well the subsets of the original factors in the FF3 and FF5 models explain stock return variations in China. Among all the models we investigated, at the end of chapter 2, we will determine a "best" model, that is, the one which best explains the stock return variation in China. The difference between chapter 2 and chapter 3 is that in chapter 2 we construct factors in exactly the same way as Fama and French (2015), and then study whether different subsets of the five factors create a better model. This chapter (chapter 2) is fundamentally different from chapter 3. In chapter 3, we do two steps which are different from Fama and French (2015). In chapter 3, we do a sensitivity analysis where we do a two-stage testing of models. In the first stage, we reconstruct factors using the average returns of different portfolios representing various sizes, B/M, investment style and profitability as defined in Fama and French (2015). In other words, even though the factor definitions are the same as Fama and French (2015), the actual construction is different (see Section 3.1 of Chapter 3). In the second stage, we do another sensitivity analysis by using a set of different breakpoints on size and B/M and systematically look through the models defined by different cutting points to investigate whether any model has statistically better explanatory power. By the end of chapter 3, we hope to find the optimal set of factors in terms of portfolios involved and breakpoints determined.

Finding the optimal set of factors has implications for the Chinese stock market. Firstly, in the relevant literature, a lot of effort has been put into finding the right types of factors (derived from anomalies) to explain stock return variations (Zhang and Xu, 2014; Guo and Wang, 2014; Qi, 2018). Yet very little work has been done on finding out whether, once the anomalies were determined, defining the derived factors differently made any difference to the explanatory power of the model. Our study confirms that, yes, different factor constructions make differences, at least in the Chinese sample we studied.

Secondly, once we know that constructing factors differently does make a difference, a natural question is therefore whether ignoring this fact creates any benefit or cost to the analysis of the mutual fund performance. That is, whether using approximations, standard original constructions, or our modified constructions, brings any difference in the ranking of the mutual fund performances. This question is very important since China has a young and rapidly growing mutual fund industry, and using a poorly performing or mis-specified model to analyze mutual fund performance would be detrimental to this young industry. A fund manager may be able to generate higher returns than what his or her peers produces; however, if the manager keeps a large number of risky assets (assets with known high β) in his or her portfolio, then the fund is actually more risky than other funds. Therefore, an appropriate ranking of mutual funds which takes into account the risks held is very important to this young industry.

The momentum factor of the Carhart four-factor model is not examined in detail in this thesis. However, a preliminary analysis (in Section A.1 of the Appendix) showed that the momentum factor was unlikely to be a stable factor judged by regressions – a similar finding to Yang et al. (2018). Another reason to exclude the consideration of the momentum factor is that short selling is not feasible in the Chinese stock markets (China Securities Regulatory Commission).

So gains from short-selling under-performing stocks are not available to Chinese fund managers.

The remainder of this chapter is set up as follows: Section 2.1 describes the data used. Section 2.2 explains the dependent variables of the models – the double-sorted portfolios. Section 2.3 describes the independent variables – the factors. Section 2.4 runs the regressions and analyzes model performances. Section 2.5 concludes.

2.1 Data – Full Dataset

The model we use in this study is as follows:

$$R_{i,t} - R_{F,t} = a_i + b_i(R_{M,t} - R_{F,t}) + s_i SMB_t + h_i HML_t + r_i RMW_t + c_i CMA_t + e_{i,t} \tag{2.1}$$

The Market Factor $R_{M,t} - R_{F,t}$, which is the excess return of the market over the monthly risk-free rate (10-year government bond yield). The proxy for the return of the market is the log returns of the monthly prices of the CSI300. The CSI 300 is a capitalization-weighted stock market index. It is designed to replicate the performance of the top 300 stocks traded in both the Shanghai and Shenzhen stock exchanges.

The Size Factor SMB_t, is the return of portfolios mimicking small market capitalization stocks minus the returns of portfolios mimicking big market capitalization stocks. In Datastream, market value is calculated as the share price multiplied by the number of ordinary shares on issue.

The Book-to-Market Factor HML_t, which is constructed using weighted returns of portfolios of high book-to-market ratio stocks minus the returns of portfolio of stocks with low book-to-market ratios.

The Profitability Factor RMW_t, which was calculated by dividing profit by current assets. For the portfolios formed in year t, we used the returns of portfolios of stocks with high (robust) profitability minus the returns of portfolios of stocks with weak profitability. The profitability for t is calculated as the annual revenues at t minus cost of goods sold, interest expenses, and selling, general, and administrative expenses at t, all divided by book equity at the end of year $t-1$.

The Investment Style Factor CMA_t, for the portfolios formed in year t, we used the growth of total assets for the fiscal year ending $t-1$ divided by total assets at the end of $t-2$. A company's conservative investment style indicates that the company is "conservative" at investing its profits into growing the business. In other words, it spent only a small portion of its profits on expanding the business. On the other hand, a company's aggressive investment style indicates that the company is "aggressive" at investing its profit into growing the business. In other words, they spent a big portion of their profit on expanding the business.

The data were collected from Datastream (Thomson Reuters Datastream (accessed: April 2016)). For stocks return data, we first collected monthly prices of all stocks listed on the Shanghai Stock Exchange and the Shenzhen Stock Exchange during December 2007 to December 2016, then we transformed these prices into monthly holding returns using the formula $r_{i,t} = (P_{i,t} - P_{i,t-1})/P_{i,t-1}$ where $r_{i,t}$ is the return of the stock i at time t, $P_{i,t}$ is the price of stock i at time t, and $P_{i,t-1}$ is the price of stock i at time $t-1$. The factors tested in this section include the market factor, the size factor, the book-to-market factor, the profitability factor and the investment style factor. The first three factors were mentioned in Fama and French (1993) and all five factors were mentioned in Fama and French (2015).

2.2 The Diversified Portfolios – The Dependent Variables

Firstly, we examine the candidates for the left-hand side variables of the regression models, which is the monthly excess returns of the three sets of 16 diversified portfolios that are double-sorted on three different pairs of variables. We follow the method of creating portfolios described in Fama and French (2015). The number of double sorted portfolios was 25 in this paper. However, when we split all stocks into 25 portfolios, some of the portfolios in the highest quantile were empty due to the limited number of stocks we were studying. Therefore, we split stocks into only 16 portfolios.

Panel A of Table 2.1 shows the average monthly excess returns of the 16 value-weighted portfolios sorted by size and B/M ratio. The B/M ratio is sorted in columns and the size is sorted in rows. Both the size and the B/M ratio are sorted into 4 equal quantiles using the full data set. A total of 8761 stocks were studied for the full period between December 2007 and December 2016. At first glance, the excess returns increase systematically as size decreases. The extreme effect of size and B/M ratio is shown in column 2 row 4 - companies with the biggest size and the second lowest B/M have a return of -0.002 (-0.2%) per month. This is contrary to what the US data shows. Fama and French (2015) show that although excess returns shown in column 1 were unexpected, the extreme big stocks with extreme small B/M were not significantly different from stocks in the rest of the column (0.46% compared with 0.26%, 0.48%, 0.50% and 0.60% in Table 1 on page 3 of Fama and French (2015)). Panel A of Table

2.1 is also displayed in Figure 2.1. As we can see from Figure 2.1, the size effect is quite clear but the B/M effect is not.

Panel B of Table 2.1 shows the average monthly excess returns (as decimals) of the 16 value-weighted portfolios sorted by size and profitability. The sizes were sorted in the rows and the profitability in the columns. There is a clear size effect and little profit effect in panel B. Hold profitability constant, and the returns decrease as the size increases. Hold size constant, and the returns do not have systematic patterns. In the smallest size quantile, the portfolios with the lowest and highest operating profit have a slightly higher excess returns of 0.023 (2.3%) per month compared with the rest of the portfolios in the same row. In the largest size quantile, that is, in the last row, there is a distortion of this pattern: the stocks that were in the largest size quantile but in the second-smallest profit quantile have an average monthly excess return of -0.1%, which is much smaller than the returns of the rest of the stocks in the largest size quantile. Panel B of Table 2.1 is also shown graphically in Figure 2.2. As we can see from Figure 2.2, the size effect is quite clear but the profitability effect is not.

Panel C of Table 2.1 shows the average monthly excess returns (as decimals) of the 16 value-weighted portfolios sorted on size and investment style. The size quantiles are displayed and varied by rows and the investment style quantiles are displayed and varied by columns. For portfolios formed in December of year t, investment style is the growth of total assets for the financial year ended in year $t-1$ divided by total assets at the end of the financial year $t-2$. Note that the investment style factor is the only factor that uses figures from two years back, because it measures the growth of an investment level. The size effect is still clear but the investment-style pattern is not. Holding the investment-style constant, the larger the size the smaller the average returns of the stocks. Holding size constant, we could not detect any reasonable patterns of returns that would indicate investment style was a factor that influenced average portfolio returns. Similar to panel B of Table 2.1, the portfolios in the largest size quantile and the third investment-style quantile have the lowest average return of -0.1% per month which was mostly due to the size effect. For all size quantiles, there is no systematic change in returns between the smallest investment-style quantile and the largest investment-style quantile. Panel C of Table 2.1 is also displayed in Figure 2.3. As we can see from Figure 2.3 the size effect is quite clear but the investment-style effect is not.

To analyze the four factors further, we also split portfolios in two according to their size as in Fama and French (2015). This way, a three-dimensional sorting becomes possible. Table 2.2 shows average excess returns for the 32 size-B/M-OP portfolios, the 32 size-B/M-investment-style portfolios, and the 32 size- OP-investment-style portfolios. Notice that the panel B of Table 2.2 has an empty cell in row 2 column 8 of the table. This result comes from the fact that portfolios were simultaneously sorted rather than sequentially sorted. As shown in panel A of Table 2.2, for both the small stocks and big stocks groups, there are no clear value (high B/M ratios) and profitability (OP) effects. That is, hold OP constant, and average returns shows no systematic pattern as B/M increases; hold B/M constant, and the returns have no discernible patterns as the OP increases. As shown in panel B of Table 2.2, for both the small stocks and big stocks groups, there are no clear value (high B/M ratios) and investment style effects. In panel C of Table 2.2, the result is the same. There is no discernible pattern in the returns.

Table 2.1: The average monthly excess returns (as a decimal) of the 16 value weighted portfolios sorted between size and B/M ratio, size and profitability, and size and investment-style.

	Low	2	3	High
Panel A: Size - B/M Portfolios				
Small	0.022	0.021	0.022	0.021
2	0.014	0.014	0.015	0.014
3	0.008	0.009	0.010	0.009
Big	0.000	-0.002	0.001	0.001
Panel B: Size - OP Portfolios				
Small	0.023	0.020	0.020	0.023
2	0.015	0.015	0.014	0.016
3	0.008	0.007	0.011	0.009
Big	0.002	0.000	-0.001	0.001
Panel C: Size - Inv Portfolio				
Small	0.022	0.022	0.020	0.023
2	0.016	0.014	0.016	0.013
3	0.009	0.010	0.009	0.009
Big	0.003	0.000	-0.001	0.000

The average monthly excess returns (as a decimal) of the 16 value weighted portfolios sorted between size and B/M ratio, size and profitability, and size and investment-style. Panel A shows the average monthly excess returns of the 16 value-weighted portfolios sorted by size and B/M ratio. The B/M ratio is sorted in columns and the size is sorted in rows. Both the size and the B/M ratio are sorted into 4 equal quantiles using the full data set. A total of 8761 stocks were studied for the full period between December 2007 and December 2016. Panel B shows the average monthly excess returns (as decimals) of the 16 value weighted portfolios sorted by size and profitability. The sizes were sorted in the rows and the profitability in the columns. Panel C shows the average monthly excess returns (as decimals) of the 16 value weighted portfolios sorted on size and investment style. The size quantiles are displayed in rows and the investment style quantiles are displayed in columns.

Table 2.2: Average excess returns (as decimals) for the 32 size-B/M-OP portfolios, the 32 size-B/M-investment portfolios, and the 32 size-OP-investment portfolios.

	Small				**Big**			
Panel A: Portfolios formed on Size, B/M and OP								
B/M->	Low	2	3	High	Low	2	3	High
Low OP	0.017	0.017	0.019	0.018	0.004	0.004	0.004	0.003
2	0.019	0.016	0.018	0.016	0.001	0.002	0.004	0.003
3	0.020	0.018	0.016	0.016	0.000	-0.002	0.000	0.003
High OP	0.016	0.018	0.019	0.014	0.001	0.002	0.002	0.000
Panel B: Portfolios formed on Size, B/M and Inv								
B/M ->	Low	2	3	High	Low	2	3	High
Low Inv	0.018	0.018	0.019	0.015	0.002	0.004	0.005	0.003
2	0.016	0.016	0.020	0.017	0.007	0.000	0.003	NA
3	0.016	0.019	0.018	0.015	-0.003	-0.001	-0.002	0.002
High Inv	0.019	0.016	0.016	0.016	0.000	0.002	0.007	-0.001
Panel C: Portfolios formed on Size, OP and Inv								
OP->	Low	2	3	High	Low	2	3	High
Low Inv	0.020	0.014	0.018	0.020	0.005	0.005	0.000	0.007
2	0.017	0.020	0.016	0.017	0.002	0.006	-0.001	0.008
3	0.019	0.016	0.017	0.018	0.007	-0.003	0.003	-0.002
High Inv	0.019	0.017	0.017	0.015	0.000	0.004	-0.002	0.004

Average excess returns (as decimals) for the 32 size-B/M-OP portfolios, the 32 size-B/M-investment portfolios, and the 32 size-OP-investment portfolios. The build up of the table is the same as Table 2.1, except before any sorting was conducted, all stocks was split into two size groups using median size of all stocks as a breakpoint. Them within each size group, sorting were conducted using the exact method as in Table 2.1.

Figure 2.1: The 3-D graph of Table 2.1 panel A. The average monthly excess returns (as a decimal) of the 16 value- weighted portfolios sorted between size and B/M ratio. The vertical axis is the return (r) of the portfolios. As can be seen from the graph, the size effect is clear but the B/M effect is not.

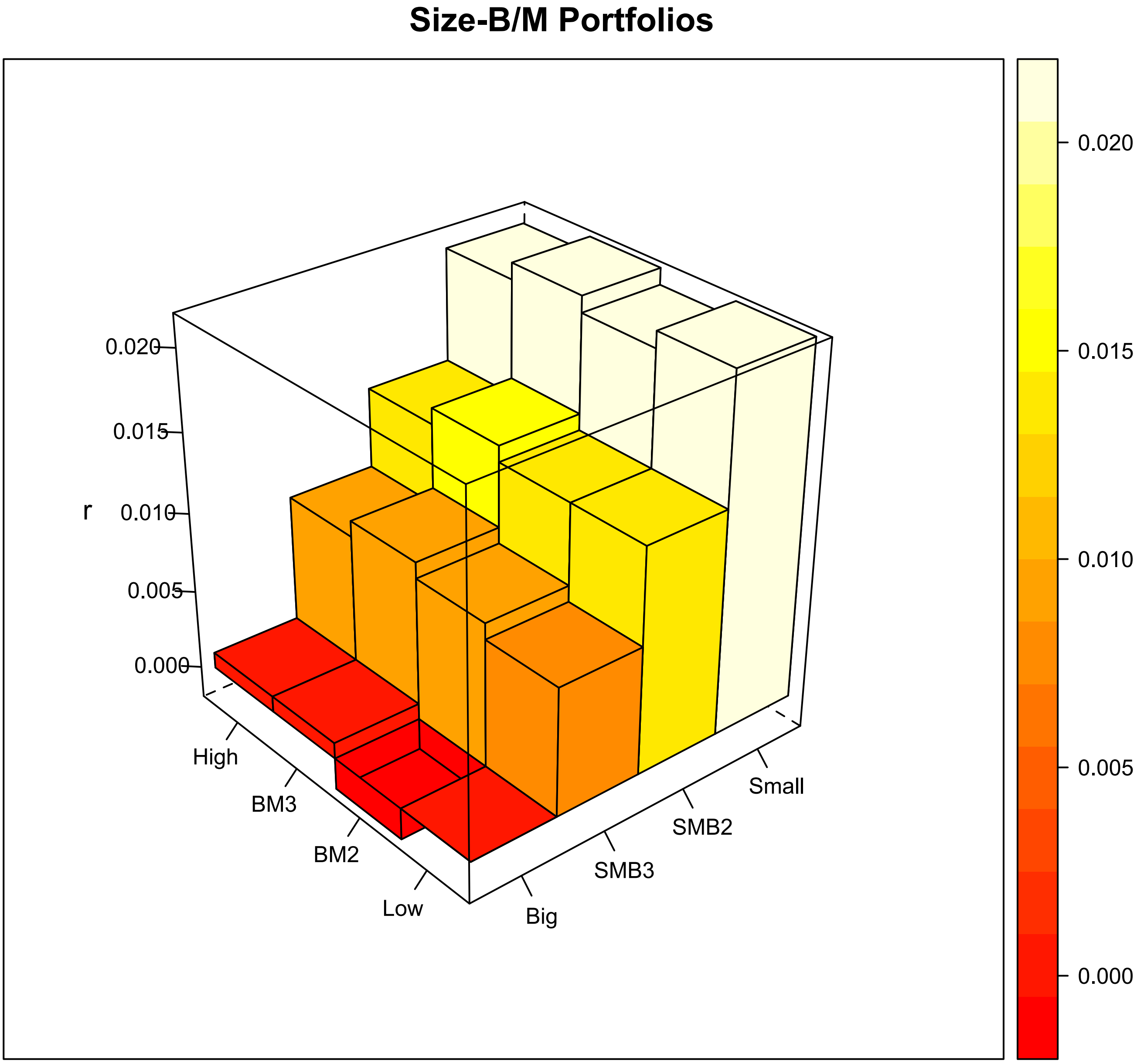


Figure 2.2: The 3-D graph of Table 2.1 panel B. The average monthly excess returns (as a decimal) of the 16 value- weighted portfolios sorted between size and profitability. The vertical axis is the return (r) of the portfolios. As can be seen from the graph, the size effect is clear but the profitability effect is not.

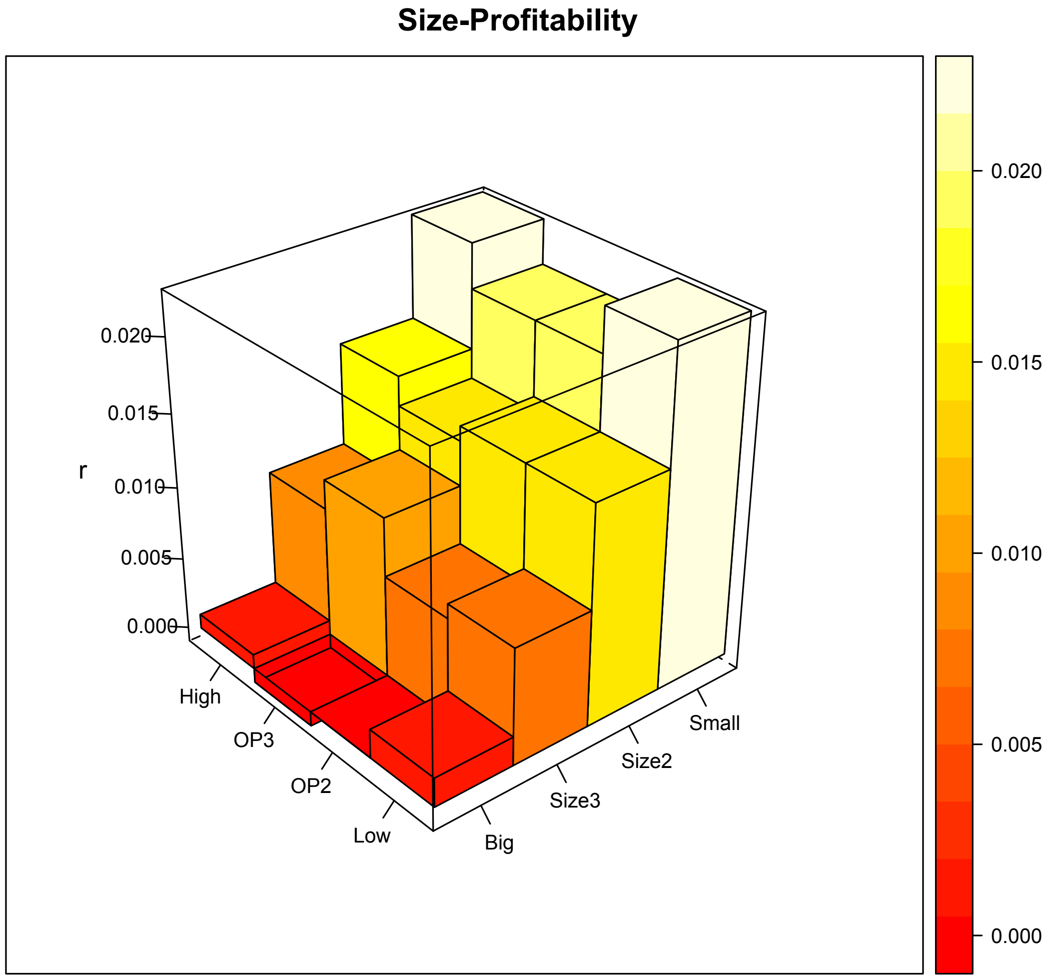
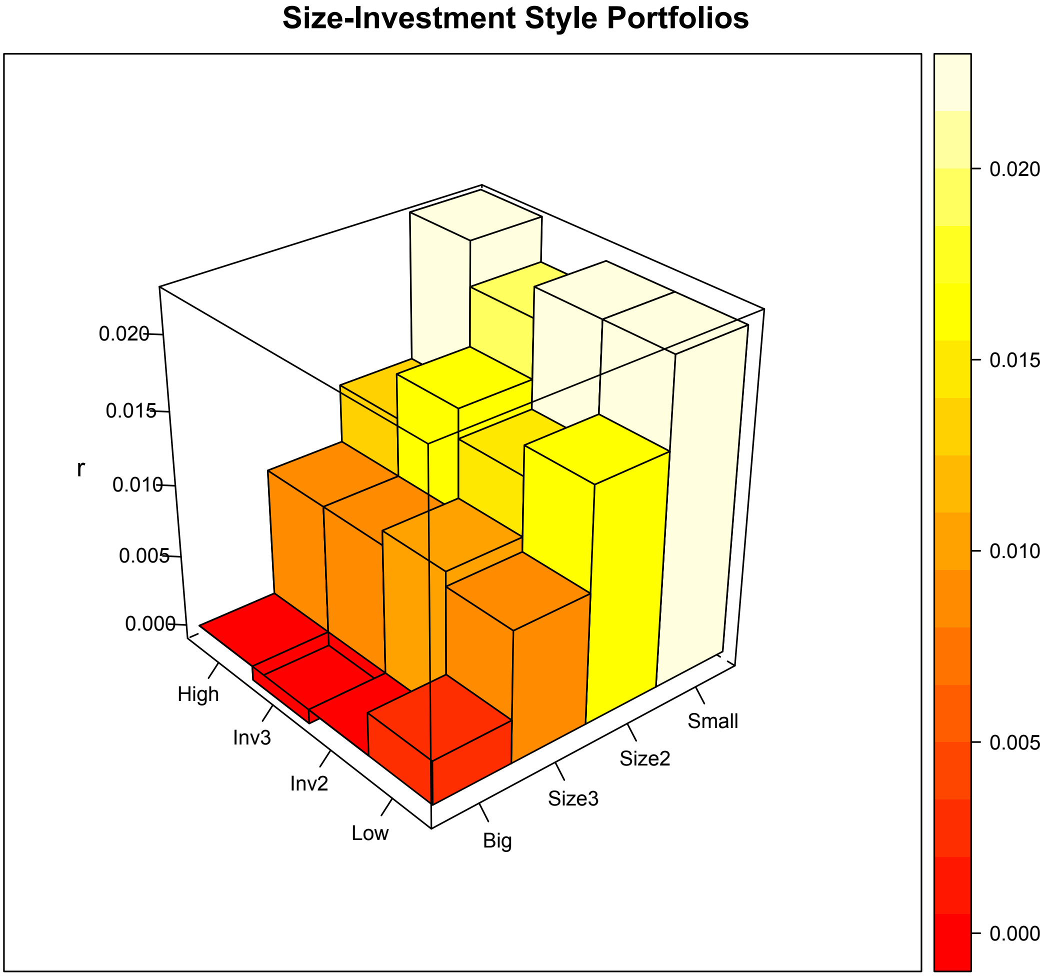


Figure 2.3: The 3-D graph of Table 2.1 panel C. The average monthly excess returns (as a decimal) of the 16 value-weighted portfolios sorted between size and investment-style. The vertical axis is the return (r) of the portfolios. As can be seen from the graph, the size effect is clear but the investment style effect is not.



2.3 The Factors – The Independent Variables

2.3.1 Factor Definitions

The **market factor** is the excess return of a market portfolio over the risk free return, where the market portfolio is a portfolio that is designed to act as a proxy for the systematic risk and therefore captures the most variation in the returns of stocks in the market. It is impossible to find a true market factor that completely captures the variation of returns of all stocks in the market. We decided to use the returns of the CSI300[1] as a proxy for the market portfolio. The ***SMB*** factor is the time series returns of portfolios of **small**-cap stocks minus the time series returns of portfolios of **big**-cap stocks. The small size stocks were those smaller than the 50th percentile of the capitalization of the stocks in the Shanghai and Shenzhen stock exchanges. The ***HML*** factor is the time series returns of portfolios of stocks with **high** book-to-market ratios minus the time series returns of portfolios of stocks with **low** book-to-market ratios. The level of B/M used to define high and low B/M was the 50th percentile of the B/M of stocks in the Shanghai and Shenzhen stock exchanges. The ***RMW*** factor is the time series returns of portfolios of stocks with **robust** profitability minus the time series returns of portfolios of stocks with **weak** profitability. The level of profitability used was the 50th percentile of the profitability of stocks in the Shanghai and Shenzhen stock exchanges. Note that the HML factor is potentially problematic. *HML* uses accounting data (*B/M* ratio) which may be unreliable in the Chinese market. This fact is described in Lin and Chen (2005), which finds that book values of owner's equity determined under International Accounting Standards (IAS) are less relevant than the Chinese Accounting Standards (CAS)

[1]The CSI 300 is a capitalization-weighted stock-market index which replicate the performance of the largest 300 stocks listed in the Shanghai and Shenzhen stock exchanges.

for the purpose of determining the prices of A- and B-shares. Yet, the CAS was largely replaced by the International Financial Reporting Standard (IFRS) in 2010.

The term profitability is measured by the accounting profit at time $t-1$ divided by book equity at year $t-1$. The accounting profit was calculated using annual revenue minus cost of goods sold minus interest expense on debt minus sales, general and administrative expenses. The ***CMA*** factor is the time series returns of portfolios of stocks with a **conservative** investment style minus the time series returns of portfolios of stocks with an **aggressive** investment style. The level of investment was calculated using the growth of total assets for year $t-1$ divided by the total assets at the end of the financial year $t-2$.

2.3.2 Factor Construction Method

The method of factor construction is exactly the same as the first factor construction method discussed in Fama and French (2015) (2×3 sort construction). Since the size factor is the most influential factor, *SMB* was calculated meticulously in two steps. In the first step, $SMB_{B/M}$, SMB_{OP} and SMB_{Inv} were calculated as follows:

$SMB_{B/M}$ was calculated by firstly independently sorting stocks into two size groups and three B/M groups. The size breakpoint is the median of all stocks studied. The B/M breakpoints are the 30^{th} percentile and 70^{th} percentile. This sort produced six value-weighted portfolios. $SMB_{B/M}$ is the average of the three small-stock portfolios returns minus the average of the three big-stock portfolios returns.

SMB_{OP} was calculated by firstly independently sorting stocks into two size groups and two operating profit groups. The size breakpoint is the median of all stocks studied. The operating profit breakpoint is the median operating profit of all stocks studied. This sort produced four value-weighted portfolios. SMB_{OP} is the average of the two small stock portfolio returns minus the average of the two big stock portfolio returns.

SMB_{Inv} was calculated by firstly independently sorting stocks into two size groups and two investment-style groups. The size breakpoint is the median of all stocks studied. The investment-style breakpoint is the median investment-style of all stocks studied. This sort produced four value-weighted portfolios. SMB_{Inv} is the average of the two small -stock portfolios returns minus the average of the two big-stock portfolios returns.

The second step is the step that calculates the *SMB* factor which is the average of $SMB_{B/M}$, SMB_{OP} and SMB_{Inv}.

For the *HML*, *RMW* and *CMA* factors, the 2×3 sort defines these factors in a simpler way as *SMB*. They were calculated using portfolios that were only sorted against the size factor. For example, the *HML* of the 2×3 sort is calculated as the weighted average return of high B/M stocks minus the weighted average return of low B/M stocks. Similar methods were applied to the *RMW* and *CMA* factors. Note when the average was weighted against value instead of simple average, the average was calculated by taking into account the weight of each stock's market capitalization. For example, a stock with a small market capitalization would only contribute a small portion in the calculation of the final mean return of the portfolios. Also note, the size breakpoint used in Fama and French (2015) was the NYSE median, the B/M, *OP* and Investment breakpoints were the 30th and 70th percentile of NYSE, respectively. In this study, instead of using an index, we use the dataset as the base to decide the breakpoints. That is, for example, we used the median point of the dataset to define the breakpoint in this study.

We do not take a strong stand on the assumption behind using the median point of the dataset instead of index to define the breakpoints. Perhaps there is no significant difference between using any index or the median point of the whole dataset, since in China, there are two stock markets, and we find it is easier to use the median point of the whole data set rather than the median point of any index.

2.3.3 Factor Statistics

The summary statistics of returns of factors are presented in Table 2.3 below. Note that as shown in Figure 2.4, during the years 2007 to 2016, the Chinese stock market had a lot of variation. The standard deviations of *SMB* and *HML* were 0.041 (4.1%) and 0.033 (3.3%) per month respectively. The mean of the market excess returns was -0.002 (-0.2%) per month. The mean of *SMB* factor was 0.016 (1.6%) per month and the mean of the *HML* was 0% per month. There is also evidence that, compared with the *SMB* and *HML* factors, the *RMW* and the *CMA* may not be factors that explain stock return variation in the Chinese stock market. The standard deviation for *RMW* was 0.025 (2.5%) per month and the standard deviation for *CMA* was 0.016 (1.6%) per month.

Panel B of Table 2.3 shows the correlations between different factors. *SMB* is highly negatively correlated with *HML* and *RMW*. The correlation between SMB and HML is -0.56 and the correlation between SMB and RMW is -0.67. Such a high (negative) correlation makes direct application of the Fama and French factor model detrimental because of the multicollinearity problem. The multicollinearity is a situation where one predictor variable in a multi- regression model can be linearly predicted from the other predictor variables in the model. It other words, when one independent variable changes, another independent variable changes with it, hence is not truly independent. In this situation, the coefficient estimates of the multiple regression may change unrealistically in response to small changes in the model or the data, which makes it difficult for the model to explain the relationship between the independent variables and the dependent variables. That is, a multivariate regression model with highly correlated predictors could still predict well the left-hand side dependent variables, but it may not give valid results about which predictors are more useful than the

Table 2.3: Summary statistics for the factors; December 2007 to December 2016, 109 months.

Panel A: Mean, std dev and t-tests					
	$R_M - R_F$	SMB	HML	RMW	CMA
Mean	-0.002	0.016	0.000	-0.001	0.003
std dev	0.091	0.041	0.033	0.025	0.016
t-test	-0.25	4.04	-0.03	-0.57	1.80

Panel B: Correlation between different factors					
	$R_M - R_F$	SMB	HML	RMW	CMA
$R_M - R_F$	1	0.04	0.08	-0.38	-0.10
SMB		1	-0.56	-0.67	0.41
HML			1	0.43	-0.08
RMW				1	-0.50
CMA					1

other. For more details, refer Goldberger and Goldberger (1991).

Figure 2.4: The Shanghai Stock Market index 1991 to 2017

2.4 Performance Analysis

2.4.1 Regression Analysis of Nine Models and Discussion

In this section, we consider a total of nine models to explain stock return variation in China. The models are: a CAPM model that contains only the market factor; four two-factor models, each containing a market factor and one of the other four factors (SMB, HML, RMW and CMA); three three-factor models, each containing the market and size factors and one factor from the remaining other three factors; and finally a five-factor model containing all five factors. As can be seen, we ignored the three-factor models excluding the size factor and four-factor models. The reason for those exclusions is that a preliminary analysis not shown in this chapter indicated they have little value in our progressive analysis. In the following section, we will discuss the regression results produced by the nine models in terms of 1) intercepts, 2) slopes and 3) adjusted R squared.

The nine models are the following:

Model 1 $R_{i,t} - R_{F,t} = a_i + b_i(R_{M,t} - R_{F,t}) + e_{i,t}$

Model 2 $R_{i,t} - R_{F,t} = a_i + b_i(R_{M,t} - R_{F,t}) + s_i SMB_t + e_{i,t}$

Model 3 $R_{i,t} - R_{F,t} = a_i + b_i(R_{M,t} - R_{F,t}) + h_i HML_t + e_{i,t}$

Model 4 $R_{i,t} - R_{F,t} = a_i + b_i(R_{M,t} - R_{F,t}) + r_i RMW_t + e_{i,t}$

Model 5 $R_{i,t} - R_{F,t} = a_i + b_i(R_{M,t} - R_{F,t}) + c_i CMA_t + e_{i,t}$

Model 6 $R_{i,t} - R_{F,t} = a_i + b_i(R_{M,t} - R_{F,t}) + s_i SMB_t + h_i HML_t + e_{i,t}$

Model 7 $R_{i,t} - R_{F,t} = a_i + b_i(R_{M,t} - R_{F,t}) + s_i SMB_t + r_i RMW_t + e_{i,t}$

Model 8 $R_{i,t} - R_{F,t} = a_i + b_i(R_{M,t} - R_{F,t}) + s_i SMB_t + c_i CMA_t + e_{i,t}$

Model 9 $R_{i,t} - R_{F,t} = a_i + b_i(R_{M,t} - R_{F,t}) + s_iSMB_t + h_iHML_t + r_iRMW_t + c_iCMA_t + e_{i,t}$

Tables 2.4 to 2.12 display the regression results of the nine models considered.

The intercepts

In the first step of our analysis, we will focus on examining the intercepts (αs). A good model should produce an α that is significantly not different from zero. We started from the basic CAPM. As can be seen in Table 2.4, the intercepts are mostly non-zero except for the large-size and low-B/M portfolios judged by the t-tests. The t-tests for the intercepts (a) at row 4 column 1 and 2 are 0.37 and -0.08, respectively. This is an indication that there are some patterns in the small portfolios that are not explained as well as in the high-B/M portfolios.

Then we added one more factor to the original CAPM to create four models (models 2 to 5 in Tables 2.5 to 2.8). Among these four models, model 2 (in Table 2.5) produced the best intercepts: the average of the absolute value of intercepts t-tests is 1.62, compared with the other three two-factor models of 3.13, 2.79, and 2.07.

Moving on from the two-factor models to the three-factor models (models 6 to 8 in Tables 2.9 to 2.11), it is clear that the three-factor models as a group produced better intercepts than the two-factor models. The Fama and French three-factor model (model 6 in Table 2.9) produced the lowest average t-test for intercepts ($t = 1.28$ on average) among all the three three-factor models.

When looking further into size groups, among the four two-factor models, model 2 (in Table 2.5) which contained the two factors of market and size, produced by far the lowest average intercept for the first eight smallest portfolios. This indicates that it is necessary to include size factor in the model to explain the patterns in the smaller portfolios. A surprising fact was found in the Fama and

French three-factor model (model 6 in Table 2.9). Among the three three-factor models, the Fama and French three-factor model produced the highest absolute value for intercepts for the first eight smallest portfolios. Therefore a conclusion can be drawn here: a two-factor model containing a market factor and a size factor produces a reasonable set of low intercepts. However, when we add in a B/M (HML) factor, the model (model 6 in Table 2.9) loses the ability to fit the returns of the portfolios, especially the smaller size portfolios.

The five-factor model in Table 2.12 produced the lowest average t-test for intercepts amongst all nine models ($t = 1.07$). However, this does not permit the conclusion that a five-factor model is the best model; slopes, adjusted R^2s and GRS tests are still needed to make better conclusions.

The Market β

Another regression outcome that has a certain expected value is the market β. As indicated by the CAPM model, the market β is expected to be one since the market factor is expected to mimic the portfolio that contains every asset in the market. From Tables 2.4, 2.6 and 2.8, we can see that models 1, 3, and 5 produced a market beta that is very close to one. (The average absolute value of t-tests for β of model 1 is 1.11, the average absolute value of t-tests for β of model 3 is 1.06 , the average absolute value of t-tests for β of model 5 is 0.95). Model 3 in Table 2.6 contains a market and an HML factor and model 5 in Table 2.8 contains a market and a CMA factor. The close-to-one βs indicate that the HML and CMA factors in Tables 2.6 and 2.8 individually do not change the original CAPM fundamentally in terms of market β. In the largest size quantile in all nine models, the t-tests of market β decreases systematically from low-B/M to high-B/M except for the highest-B/M portfolios. For example, in the CAPM of Table 2.4, the t-tests of the market β in the largest-size quantile were -2.31, -0.89,

-0.36 and -3.86. The -3.86 for the highest B/M dropped abruptly to -0.36 from the next highest-B/M ratio portfolio. One interesting phenomenon is that the t-test scores for the two corner portfolios (the smallest-size and lowest-B/M portfolio, and the large-size and high-B/M portfolio) are vastly different despite the fact that their actual values for the intercepts are similar. This indicates that the standard deviation of the returns for the large-size and high-B/M portfolios is much smaller than that of the small-size and low-B/M portfolios. In other words, the stocks with large capitalization and high B/M are more homogeneous.

The β for the other four factors

Except the market β, which we know the theoretical expected value of, we do not know the expected theoretical value of β for the other four factors. But at least we could discuss their signs and magnitude in the regression results to get a better understanding of the factors' function and influence in the models. The sign ("+" or "-") of βs represents the types of characteristics of stocks that influence stock returns, and the magnitude of the β represents the level of these influences. We will discuss the β for each of the four factors next.

The size factor can be found in Tables 2.5, 2.9, 2.10, 2.11 and 2.12. Looking through these tables, we see that the βs of the size factor are mostly positive and above 1. This means the returns of the stock portfolios were influenced by the small stocks more strongly than by the big stocks, and these influences were quite strong, especially so as the capitalization of stocks in the portfolio decreases. There are some exceptions: in the last row (the row contains stocks of the largest capitalization), the β of the size factor has smaller magnitudes; in some cases of the largest and highest book-to-market ratio portfolios (L4H4), there were even negative size βs. These negative βs indicate that the influence from the smaller stocks was weak in these large-cap portfolios, and the negative sign indicates that the portfolio was influenced by, however, the big-stock portfolios instead of small-stock portfolios. Such negative size βs may be easy to interpret: during the privatization process of the Chinese stock markets, some of the large-cap listed stocks were state-owned enterprises, who suffered loss or did not attract investors' interest or trust after being listed. These stocks had an essentially different growth trajectory from the smaller stocks, and therefore were influenced more by their peers (the big stocks). This phenomenon creates a problem for our models. It is interesting to note that instead of having a problem in the small stock as specified in Fama and French (2015), the models have problem in big stocks in China, which indicates that China may be fundamentally different from the markets around the rest of the world.

The β of the B/M factor (HML) can be found in Tables 2.6,2.9, and 2.12. At first glance, they are mostly negative in sign and mostly above 1. The negative signs indicate that the returns of most stock portfolios were influenced by stocks with "low" B/M, and the above 1 magnitude indicates the influence was strong. There are again exceptions in the large-cap and high-B/M portfolios (S4L4): the HML β for this portfolio appears to be positive and small. The interpretation of this phenomenon is that in the extremely high-B/M portfolios, the high-B/M stocks had a strong influence than the low-B/M stocks, which in turn created a problem for our models.

As for the β of the RMW and CMA factors, there is not much value in taking them into account in the regression analysis, since the RMW and CMA factors were proved to be redundant factors in our model due to their lack of explanatory powers. However, if they were in fact factors, then, the negative signs of the RMW factor indicates that the returns of stock portfolios in China were influenced more by the returns of stocks with weak profitability than by the stocks with rapid profitability. And the negative signs of the CMA factor indicate that the returns of the stock portfolios in China were influenced more by stocks with an aggressive investment style than by the stocks with a conservative investment style.

The adjusted R^2

The adjusted R^2 is one of the most important factors to decide whether a regression model is a good model. The higher the adjusted R^2, the "better" the model. The original CAPM in Table 2.4 has an average adjusted R^2 of 72.38%, which indicates a reasonably good explanatory power. In particular, the adjusted R^2s increases systematically as the capitalization of stocks in portfolios increases. This indicates that the CAPM is an incomplete model to explain the portfolio returns – there are patterns in adjusted R^2s unexplained by the market factor. When we included an extra size factor (SMB) shown in Table 2.5, the model's average explanatory power jumped dramatically to 93.25%. However, the other three two-factor models do not have as high an adjusted R^2. Their average R^2s are 84.44%, 84.94% and 74.81%, respectively (Tables 2.6, 2.7 and 2.8). Moving on to the three-factor models, the average adjusted R^2s increased again to 95.25%, 93.63% and 93.63%, respectively for the models in Table 2.9 to 2.11. Including a third factor does not increase the adjusted R^2 by much over market plus SMB but instead, created a multicollinearity problem. Similarly, the five-factor model has an adjusted R^2 of 95.63% – not a statistically significant increase from the two-factor model containing a market factor and a size factor (93.25%). In other words, the 2.38% increase in explanatory power (adjusted R^2) for including three more factors is not a beneficial trade-off[2]. Overall, there is an indication that a two-factor model containing a market factor and a size factor (in Table 2.5) may be the best model among all nine models considered.

Regression conclusion

[2]Note that even though the adjusted R^2 is the R^2 adjusted by an adjustment factor ($n - 1/n - p - 1$, where n is the number of observations and p is the number of variables), the adjustment factor is close to one due to the size of n and p.

It is clear that the RMW and CMA are not good factors to explain the stock return variation in China. This result comes from the regression results of model 4 and 5 in Tables 2.7 and 2.8.

Therefore, the candidates for the winning model is the two-factor model containing a market factor and a size factor. We will combine the GRS (Gibbons et al., 1989) tests to analyze further to decide which model is the best model to explain the stock return variation in China.

Table 2.4: Regressions of the 16 value-weighted Size-B/M sorted portfolios; December 2007 to December 2016. At the end of each month, four size (from small to big) intervals and four B/M (from low to high) intervals are determined independently. Stocks that fit each of the total sixteen resulting intervals are formed as portfolios, therefore a total of 16 portfolios are formed. We take their monthly excess returns as a decimal as the left hand side (LHS) variable in the regression. The right hand side (RHS) variable of the regression is the market factor from the CAPM:

$$R_{i,t} - R_{F,t} = a_i + b_i(R_{M,t} - R_{F,t}) + e_{i,t}$$

Model 1

	Low	B/M 2	B/M 3	High	Low	B/M 2	B/M 3	High
	a (Intercept)				**t(a)**			
Small	0.024	0.023	0.024	0.023	3.85	3.55	3.75	3.80
2	0.016	0.017	0.017	0.017	2.69	2.77	3.08	3.38
3	0.010	0.012	0.012	0.012	1.65	2.07	2.33	2.99
Big	0.002	0.000	0.003	0.003	0.37	-0.08	1.20	1.08
	b (Market factor)				**t(b)** ($h_0 = 1$)			
Small	0.88	0.92	0.95	0.92	-1.73	-1.11	-0.72	-1.20
2	0.94	0.96	0.96	0.99	-0.90	-0.61	-0.65	-0.18
3	0.91	0.94	1.01	1.03	-1.36	-0.98	0.18	0.70
Big	0.89	0.97	0.99	0.89	-2.31	-0.89	-0.36	-3.86

adjusted R-squared

	Low	B/M 2	B/M 3	High
Small	0.60	0.60	0.63	0.64
2	0.65	0.66	0.69	0.75
3	0.63	0.68	0.75	0.84
Big	0.76	0.88	0.92	0.90

Table 2.5: Regressions of the 16 value-weighted Size-B/M sorted portfolios; December 2007 to December 2016. At the end of each month, four size (from small to big) intervals and four B/M (from low to high) intervals are determined independently. Stocks that fit each of the total sixteen resulting intervals are formed as portfolios, therefore a total of 16 portfolios are formed. We take their monthly excess returns as a decimal as the LHS variable in the regression. The RHS variables of the regressions are the two factors from below model including a Market factor and a size factor:

$$R_{i,t} - R_{F,t} = a_i + b_i(R_{M,t} - R_{F,t}) + s_i SMB_t + e_{i,t}$$

Model 2

	Low	B/M 2	B/M 3	High	Low	B/M 2	B/M 3	High
	a (Intercept)				**t(a)**			
Small	0.001	0.000	0.000	0.000	0.46	-0.63	-0.07	0.16
2	-0.006	-0.010	0.000	0.000	-2.59	-2.59	-1.55	-1.12
3	-0.011	-0.010	-0.010	0.000	-3.57	-2.72	-2.36	-1.05
Big	-0.009	-0.010	0.000	0.000	-2.35	-2.56	0.49	1.64
	b (Market factor)				**t(b)** ($h_0 = 1$)			
Small	0.85	0.89	0.92	0.89	-4.96	-4.40	-3.24	-4.38
2	0.91	0.93	0.94	0.96	-3.58	-2.99	-2.51	-2.17
3	0.88	0.91	0.99	1.01	-3.71	-2.99	-0.37	0.49
Big	0.88	0.96	0.99	0.89	-3.11	-1.41	-0.36	-3.90
	s (Size)				**t(s)**			
Small	1.46	1.57	1.52	1.43	21.37	27.98	27.31	25.34
2	1.44	1.42	1.33	1.18	25.52	27.07	24.85	28.44
3	1.35	1.24	1.14	0.87	18.50	18.24	19.02	18.75
Big	0.66	0.43	0.11	-0.11	7.63	6.80	1.75	-1.71

adjusted R-squared

	Low	B/M 2	B/M 3	High
Small	0.92	0.95	0.95	0.95
2	0.95	0.96	0.95	0.97
3	0.91	0.92	0.94	0.96
Big	0.85	0.92	0.92	0.90

Table 2.6: Regressions of the 16 value-weighted Size-B/M sorted portfolios; December 2007 to December 2016. At the end of each month, four size (from small to big) intervals and four B/M (from low to high) intervals are determined independently. Stocks that fit each of the total sixteen resulting intervals are formed as portfolios, therefore a total of 16 portfolios are formed. We take their monthly excess returns as a decimal as the LHS variable in the regression. The RHS variables of the regressions are the two factors including a Market factor and a HML factor:

$$R_{i,t} - R_{F,t} = a_i + b_i(R_{M,t} - R_{F,t}) + h_i HML_t + e_{i,t}$$

Model 3

	Low	B/M 2	B/M 3	High	Low	B/M 2	B/M 3	High
	a (Intercept)				**t(a)**			
Small	0.024	0.023	0.024	-0.25	5.58	4.79	5.05	4.71
2	0.016	0.017	0.017	-0.65	3.73	3.60	3.85	3.90
3	0.010	0.012	0.012	-0.77	2.41	2.82	2.95	3.22
Big	0.002	0.000	0.003	-0.44	0.73	-0.13	1.21	1.39
	b (Market factor)				**t(b)** ($h_0 = 1$)			
Small	0.93	0.96	0.99	0.96	-1.45	-0.75	-0.19	-0.74
2	0.98	0.99	0.99	1.01	-0.41	-0.20	-0.20	0.21
3	0.95	0.97	1.04	1.04	-1.10	-0.67	0.90	1.01
Big	0.93	0.99	0.99	0.88	-2.91	-0.47	-0.37	-5.34
	h (B/M)				**t(s)**			
Small	-1.44	-1.39	-1.35	-1.13	-10.94	-9.44	-9.44	-7.66
2	-1.33	-1.20	-1.07	-0.78	-9.98	-8.63	-7.83	-6.06
3	-1.39	-1.19	-0.99	-0.47	-11.12	-9.65	-8.12	-4.29
Big	-1.18	-0.75	-0.15	0.51	-17.90	-12.76	-2.05	8.34

adjusted R-squared

	Low	B/M 2	B/M 3	High
Small	0.81	0.78	0.80	0.76
2	0.82	0.80	0.80	0.82
3	0.83	0.83	0.84	0.87
Big	0.94	0.95	0.92	0.94

Table 2.7: Regressions of the 16 value-weighted Size-B/M sorted portfolios; December 2007 to December 2016. At the end of each month, four size (from small to big) intervals and four B/M (from low to high) intervals are determined independently. Stocks that fit each of the total sixteen resulting intervals are formed as portfolios, therefore a total of 16 portfolios are formed. We take their monthly excess returns as a decimal as the LHS variable in the regression. The RHS variables of the regressions are the two factors including a Market factor and a RMW factor:

$$R_{i,t} - R_{F,t} = a_i + b_i(R_{M,t} - R_{F,t}) + r_i RMW_t + e_{i,t}$$

Model 4

	Low	B/M 2	B/M 3	High	Low	B/M 2	B/M 3	High
	a (Intercept)				**t(a)**			
Small	0.021	0.020	0.021	0.020	4.54	4.33	4.60	4.54
2	0.013	0.014	0.015	0.014	3.26	3.13	3.56	4.01
3	0.006	0.009	0.009	0.010	1.59	2.14	2.54	3.48
Big	0.000	-0.002	0.003	0.003	0.02	-0.63	1.07	1.13
	b (Market factor)				**t(b)** ($h_0 = 1$)			
Small	0.69	0.71	0.74	0.73	-5.55	-5.30	-4.94	-5.16
2	0.73	0.77	0.78	0.83	-5.66	-4.47	-4.57	-4.06
3	0.72	0.77	0.85	0.90	-5.38	-4.67	-3.42	-3.06
Big	0.80	0.88	0.97	0.90	-4.41	-4.13	-1.02	-3.24
	r (profitability)				**t(r)**			
Small	-1.90	-2.08	-2.01	-1.85	-9.47	-10.61	-10.54	-9.77
2	-2.03	-1.81	-1.72	-1.53	-11.81	-9.74	-9.83	-10.11
3	-1.85	-1.66	-1.56	-1.21	-9.90	-9.43	-9.94	-10.22
Big	-0.94	-0.82	-0.21	0.09	-5.77	-7.79	-1.99	0.77

adjusted R-squared

	Low	B/M 2	B/M 3	High
Small	0.78	0.80	0.82	0.81
2	0.85	0.82	0.84	0.87
3	0.81	0.83	0.87	0.92
Big	0.82	0.93	0.92	0.90

Table 2.8: Regressions of the 16 value-weighted Size-B/M sorted portfolios; December 2007 to December 2016. At the end of each month, four size (from small to big) intervals and four B/M (from low to high) intervals are determined independently. Stocks that fit each of the total sixteen resulting intervals are formed as portfolios, therefore a total of 16 portfolios are formed. We take their monthly excess returns as a decimal as the LHS variable in the regression. The RHS variables of the regressions are the two factors including a Market factor and a CMA factor:

$$R_{i,t} - R_{F,t} = a_i + b_i(R_{M,t} - R_{F,t}) + c_i CMA_t + e_{i,t}$$

Model 5

	Low	B/M 2	B/M 3	High	Low	B/M 2	B/M 3	High
	a (Intercept)				**t(a)**			
Small	0.021	0.019	0.020	0.019	3.40	3.07	3.30	3.34
2	0.012	0.014	0.014	0.013	2.15	2.33	2.62	2.88
3	0.007	0.009	0.009	0.009	1.20	1.66	1.90	2.42
Big	0.001	-0.001	0.003	0.003	0.33	-0.34	1.11	1.00
	b (Market factor)				**t(b)** ($h_0 = 1$)			
Small	0.91	0.95	0.98	0.95	-1.34	-0.73	-0.30	-0.78
2	0.97	0.98	0.98	1.01	-0.48	-0.31	-0.34	0.20
3	0.93	0.95	1.02	1.05	-1.08	-0.84	0.37	1.27
Big	0.90	0.97	0.99	0.89	-2.06	-0.89	-0.36	-3.83
	c (Investment)				**t(c)**			
Small	1.29	1.41	1.26	1.30	3.42	3.65	3.32	3.64
2	1.45	1.06	1.09	1.16	4.11	2.95	3.23	4.02
3	1.02	0.86	0.86	1.04	2.81	2.55	2.79	4.70
Big	0.06	0.29	0.06	0.06	0.21	1.52	0.37	0.37

adjusted R-squared

	Low	B/M 2	B/M 3	High
Small	0.63	0.64	0.66	0.68
2	0.69	0.69	0.72	0.79
3	0.66	0.70	0.77	0.87
Big	0.76	0.89	0.92	0.90

Table 2.9: Regressions of the 16 value-weighted Size-B/M sorted portfolios; December 2007 to December 2016. At the end of each month, four size (from small to big) intervals and four B/M (from low to high) intervals are determined independently. Stocks that fit each of the total sixteen resulting intervals are formed as portfolios, therefore a total of 16 portfolios are formed. We take their monthly excess returns as a decimal as the LHS variable in the regression. The RHS variables of the regressions are the three factors including a Market factor, a SMB factor and a HML factor:

$$R_{i,t} - R_{F,t} = a_i + b_i(R_{M,t} - R_{F,t}) + s_i SMB_t + h_i HML_t + e_{i,t}$$

Model 6

	Low	B/M 2	B/M 3	High	Low	B/M 2	B/M 3	High
	a (Intercept)				**t(a)**			
Small	0.006	0.002	0.003	0.002	2.47	0.75	1.36	0.76
2	-0.003	-0.004	-0.002	-0.002	-1.36	-1.67	-0.88	-1.31
3	-0.006	-0.004	-0.004	-0.004	-2.46	-1.65	-1.60	-1.78
Big	-0.001	-0.002	0.002	0.000	-0.48	-1.08	0.79	-0.07
	b (Market factor)				**t(b)** ($h_0 = 1$)			
Small	0.88	0.91	0.94	0.90	-4.91	-4.11	-2.76	-4.03
2	0.93	0.94	0.95	0.96	-3.30	-2.75	-2.14	-2.14
3	0.91	0.93	1.00	1.01	-3.41	-2.60	0.00	0.50
Big	0.92	0.98	0.99	0.87	-3.42	-0.95	-0.36	-6.01
	s (Size)				**t(s)**			
Small	1.16	1.37	1.32	1.34	17.67	23.24	22.55	19.99
2	1.22	1.28	1.23	1.21	21.31	21.66	19.55	23.95
3	1.04	1.01	1.01	0.96	14.60	13.87	14.53	17.73
Big	0.17	0.13	0.05	0.19	2.71	2.48	0.72	3.23
	h (B/M)				**t(h)**			
Small	-0.64	-0.44	-0.43	-0.20	-7.89	-6.05	-5.96	-2.46
2	-0.48	-0.31	-0.21	0.06	-6.83	-4.31	-2.77	0.92
3	-0.67	-0.49	-0.29	0.20	-7.62	-5.47	-3.34	3.00
Big	-1.06	-0.66	-0.12	0.64	-13.66	-9.45	-1.27	9.00

adjusted R-squared

	Low	B/M 2	B/M 3	High
Small	0.95	0.96	0.97	0.95
2	0.96	0.96	0.96	0.97
3	0.94	0.94	0.95	0.97
Big	0.94	0.96	0.92	0.94

Table 2.10: Regressions of the 16 value-weighted Size-B/M sorted portfolios; December 2007 to December 2016. At the end of each month, four size (from small to big) intervals and four B/M (from low to high) intervals are determined independently. Stocks that fit each of the total sixteen resulting intervals are formed as portfolios, therefore a total of 16 portfolios are formed. We take their monthly excess returns as a decimal as the LHS variable in the regression. The RHS variables of the regressions are the three factors including a Market factor, a SMB factor and a RMW factor:

$$R_{i,t} - R_{F,t} = a_i + b_i(R_{M,t} - R_{F,t}) + s_i SMB_t + r_i RMW_t + e_{i,t}$$

Model 7

	Low	B/M 2	B/M 3	High	Low	B/M 2	B/M 3	High
	a (Intercept)				**t(a)**			
Small	0.002	0.000	0.001	0.001	0.82	0.003	0.54	0.51
2	-0.004	-0.005	-0.003	-0.001	-1.60	-2.20	-1.12	-0.67
3	-0.009	-0.007	-0.005	-0.001	-2.91	-2.17	-1.72	-0.35
Big	-0.008	-0.004	0.002	0.005	-1.94	-1.59	0.75	1.73
	b (Market factor)				**t(b)** ($h_0 = 1$)			
Small	0.83	0.86	0.89	0.88	-4.99	-5.06	-4.02	-4.21
2	0.86	0.92	0.92	0.95	-5.28	-3.02	-2.99	-2.40
3	0.84	0.89	0.95	0.99	-4.47	-3.24	-1.69	-0.44
Big	0.86	0.90	0.97	0.89	-3.20	-3.36	-0.97	-3.40
	s (Size)				**t(s)**			
Small	1.36	1.44	1.39	1.36	14.23	18.59	18.12	17.07
2	1.22	1.36	1.25	1.12	16.50	18.41	16.66	19.18
3	1.18	1.12	1.01	0.75	11.73	11.78	12.13	11.79
Big	0.55	0.20	0.04	-0.15	4.54	2.34	0.49	-1.63
	r				**t(r)**			
Small	-0.23	-0.32	-0.31	-0.19	-1.40	-2.39	-2.32	-1.36
2	-0.53	-0.15	-0.19	-0.16	-4.16	-1.14	-1.49	-1.60
3	-0.41	-0.30	-0.33	-0.29	-2.35	-1.83	-2.31	-2.67
Big	-0.26	-0.58	-0.16	-0.09	-1.25	-3.99	-1.06	-0.60

adjusted R-squared

	Low	B/M 2	B/M 3	High
Small	0.92	0.95	0.96	0.95
2	0.96	0.96	0.95	0.97
3	0.92	0.92	0.95	0.97
Big	0.85	0.93	0.92	0.90

Table 2.11: Regressions of the 16 value-weighted Size-B/M sorted portfolios; December 2007 to December 2016. At the end of each month, four size (from small to big) intervals and four B/M (from low to high) intervals are determined independently. Stocks that fit each of the total sixteen resulting intervals are formed as portfolios, therefore a total of 16 portfolios are formed. We take their monthly excess returns as a decimal as the LHS variable in the regression. The RHS variables of the regressions are the three factors including a Market factor, a size factor and a CMA factor:

$$R_{i,t} - R_{F,t} = a_i + b_i(R_{M,t} - R_{F,t}) + s_iSMB_t + c_iCMA_t + e_{i,t}$$

Model 8

	Low	B/M 2	B/M 3	High	Low	B/M 2	B/M 3	High
	a (Intercept)				**t(a)**			
Small	0.001	-0.001	0.000	0.000	0.48	-0.62	-0.04	0.18
2	-0.006	-0.006	-0.004	-0.002	-2.58	-2.73	-1.57	-1.11
3	-0.011	-0.008	-0.006	-0.002	-3.64	-2.79	-2.41	-1.06
Big	-0.009	-0.007	0.001	0.005	-2.43	-2.55	0.49	1.63
	b (Market factor)				**t(b)** ($h_0 = 1$)			
Small	0.85	0.88	0.91	0.89	-4.92	-4.85	-3.74	-4.35
2	0.91	0.92	0.93	0.96	-3.53	-3.62	-3.00	-2.14
3	0.87	0.90	0.98	1.02	-4.08	-3.41	-0.76	0.96
Big	0.87	0.95	0.99	0.90	-3.48	-1.77	-0.36	-3.50
	s (Size)				**t(s)**			
Small	1.51	1.62	1.59	1.48	20.25	26.58	26.80	23.90
2	1.46	1.51	1.39	1.20	23.33	27.93	24.33	26.25
3	1.43	1.33	1.21	0.85	18.23	18.41	18.85	16.60
Big	0.79	0.47	0.12	-0.14	8.69	6.67	1.74	-2.06
	c (Investment)				**t(c)**			
Small	-0.31	-0.30	-0.43	-0.26	-1.66	-1.98	-2.84	-1.68
2	-0.09	-0.55	-0.39	-0.12	-0.57	-4.00	-2.68	-1.03
3	-0.49	-0.54	-0.43	0.14	-2.47	-2.98	-2.64	1.12
Big	-0.78	-0.20	-0.07	0.21	-3.40	-1.16	-0.40	1.21

adjusted R-squared

	Low	B/M 2	B/M 3	High
Small	0.92	0.95	0.96	0.95
2	0.95	0.96	0.96	0.97
3	0.92	0.93	0.95	0.96
Big	0.86	0.92	0.92	0.90

Table 2.12: Regressions of the 16 value-weighted Size-B/M sorted portfolios; December 2007 to December 2016. At the end of each month, four size (from small to big) intervals and four B/M (from low to high) intervals are determined independently. Stocks that fit each of the total sixteen resulting intervals are formed as portfolios, therefore a total of 16 portfolios are forms. We take their monthly excess returns as a decimal as the LHS variable in the regression. The RHS variables of the regressions are the five factors including a Market factor, a size factor, a HML factor, a return on asset factor (RMW) and an investment style factor (CMA): $R_{i,t} - R_{F,t} = a_i + b_i(R_{M,t} - R_{F,t}) + s_i SMB_t + h_i HML_t + r_i RMW_t + c_i CMA_t + e_{i,t}$

Model 9

	Low	B/M 2	B/M 3	High	Low	B/M 2	B/M 3	High
	a (Intercept)				**t(a)**			
Small	0.006	0.003	0.004	0.003	2.53	1.30	2.03	1.12
2	-0.001	-0.003	-0.001	-0.001	-0.49	-1.31	-0.41	-0.72
3	-0.005	-0.003	-0.002	-0.002	-1.92	-1.18	-0.96	-0.97
Big	-0.001	0.000	0.003	0.001	-0.32	-0.18	1.00	0.61
	b (Market)				**t(b)** $(h_0 = 1)$			
Small	0.86	0.86	0.89	0.86	-4.59	-5.29	-4.26	-4.59
2	0.88	0.89	0.90	0.92	-4.79	-4.34	-3.57	-3.55
3	0.85	0.87	0.93	0.96	-4.72	-4.04	-2.31	-1.67
Big	0.89	0.93	0.97	0.82	-3.86	-2.83	-0.87	-6.91

	Low	B/M 2	B/M 3	High	Low	B/M 2	B/M 3	High
	s (Size)				**t(s)**			
Small	1.15	1.32	1.28	1.32	13.83	18.29	18.43	15.85
2	1.08	1.30	1.21	1.17	16.00	18.84	16.08	19.10
3	0.99	0.99	0.96	0.84	11.43	11.31	11.73	13.08
Big	0.21	-0.01	0.02	0.11	2.73	-0.08	0.16	1.51
	h (B/M)				**t(h)**			
Small	-0.61	-0.36	-0.33	-0.13	-7.00	-4.77	4.44	-1.49
2	-0.41	-0.20	-0.11	0.13	-5.76	-2.78	-1.43	2.04
3	-0.56	-0.37	-0.15	0.27	-6.19	-4.04	-1.79	3.93
Big	-0.99	-0.58	-0.08	0.72	-12.12	-8.25	-0.83	9.67
	r (Return on Asset)				**t(r)**			
Small	-0.11	-0.35	-0.42	-0.29	-0.68	-2.59	-3.17	-1.86
2	-0.49	-0.34	-0.37	-0.33	-3.81	-2.61	-2.59	-2.89
3	-0.44	-0.44	-0.54	-0.44	-2.70	-2.64	-3.50	-3.64
Big	-0.17	-0.50	-0.19	-0.41	-1.17	-4.01	-1.06	-3.05

	Low	B/M 2	B/M 3	High	Low	B/M 2	B/M 3	High
	c (Investment Style)				**t(s)**			
Small	-0.11	-0.33	-0.50	-0.36	-0.62	-2.13	-3.32	-1.98
2	-0.17	-0.63	-0.53	-0.34	-1.12	-4.25	-3.22	-2.58
3	-0.48	-0.61	-0.64	-0.19	-2.55	-3.21	-3.60	-1.37
Big	-0.46	-0.22	-0.13	-0.29	-2.72	-1.51	-0.64	-1.90

adjusted R-squared

	Low	B/M 2	B/M 3	High
Small	0.95	0.97	0.97	0.95
2	0.97	0.97	0.96	0.97
3	0.95	0.94	0.95	0.97
Big	0.95	0.96	0.92	0.95

2.4.2 GRS Tests Analysis of Nine Models and Discussion

The GRS test was created by Gibbons et al. (1989) and is aimed at examining whether the intercepts of a multivariate regression are jointly zero, because if a multi-factor model completely captures the left-hand-side portfolios' excess returns, the regression's intercepts should be jointly close to zero.

$$GRSscore = \left(\frac{T}{N}\right)\left(\frac{(T-N-L)}{T-L-1}\right)\left[\frac{\widehat{\alpha}'\widehat{\Sigma}^{-1}\widehat{\alpha}}{1+\overline{\mu}'\widehat{\Omega}^{-1}\overline{\mu}}\right] \sim F(N, T-N-L) \quad (2.2)$$

where,

1. N is the number of portfolios on the left-hand side of the regressions;
2. L is the number of factor portfolios on the right-hand side of the regressions;
3. T is the number of time periods in the time series;
4. $\widehat{\alpha}$ is the $N \times 1$ vector of estimated intercepts;
5. $\widehat{\Sigma}$ is an unbiased estimate of the residual covariance matrix;
6. $\overline{\mu}$ is the $L \times 1$ vector of the sample means of the factor portfolios;
7. $\widehat{\Omega}$ is the unbiased estimate of the factor portfolios covariance matrix.

Just like the F-test scores, the GRS test scores are assumed to follow a $\tilde{\chi}^2$ (Chi-Squared) distribution. The null hypothesis is H_0:$\alpha_i = 0$ for all i. The higher the GRS score the less likely the intercepts are jointly zero. Therefore, we are looking for low GRS scores or high tests' P-values for good models. With the N, L and T fix, the magnitude of the GRS score depends on the term $\widehat{\alpha}'\widehat{\Sigma}^{-1}\widehat{\alpha}$, where the $\widehat{\Sigma}$ is an unbiased estimate of the residual covariance matrix ($\widehat{\Sigma} = \frac{\widehat{\varepsilon}'\widehat{\varepsilon}}{T-L-1}$). The $\widehat{\Sigma}$ assigns weights to the calculation of the weighted average of intercepts αs. In this sense, the resulting weighted average α ($\widehat{\alpha}'\widehat{\Sigma}^{-1}\widehat{\alpha}$ in Equation 2.2) became "joint". For N=25 and T=168, we estimate the threshold for the GRS score is about 1.7 (Lewellen et al., 2010).

There are strong assumptions on the test: 1) the expected value of the error terms is zero, 2) the returns and the error terms are uncorrelated over time, and 3) returns are normally distributed and uncorrelated across assets. These assumptions are normally unrealistic (Lewellen et al., 2010; Cochrane, 2009).

However, in this study, we are more interested in the *comparative* performance rather than the absolute performance of the models. Therefore, even though a reasonable range of the GRS scores for accepting the null hypotheses of αs are jointly zero is about 0.61 in our study (see Figure 5 on page 21 of Lewellen et al. (2010)), and our resulting GRS scores are far beyond this level; we can still use the GRS scores to produce a useful conclusion of the models' comparative performance.

Table 2.13 shows the GRS tests (Gibbons et al., 1989) that test whether regressions' intercepts are jointly zero. Since we are testing the null hypothesis that the intercepts are jointly zero, we are looking for low test scores and non-significant (high) p-values to accept the null hypothesis. We use 0.05 as a critical value for p-value. As can be seen, most models reject the hypothesis that the intercepts are jointly zero, as seen in column 2 of Table 2.13. The p-values are mostly close to zero. The five-factor model (model 9) fares the best in the GRS test with the lowest test score of 1.28 and p-value of 0.229. The three-factor models as a group (models 6 to 8 in Tables 2.9 to 2.11) performed better than the two-factor models (models 2 to 5 in Tables 2.5 to 2.8). This is expected, since in general the more factors in the model to explain the LHS, the lower the intercepts. Within the two-factor model group, the model 2 (in Table 2.5) with a market and a size factors performed the best with a GRS test score of 2.01. An interesting fact is that the model 3 (in Table 2.6) that contains a market factor and an HML factor performed almost the same as the CAPM model: its GRS score is 3.03 compared with 3.05 for the CAPM model (in Table 2.4). Similarly, model 4 (in Table 2.7), with a market factor and an RMW factor, produced an even worse GRS test score compared with the CAPM (in Table 2.4).

Column 3 of Table 2.13 shows the absolute value of the intercept for each model. The results were similar to that of column 2. The five-factor model produced the lowest average absolute intercept, and as a group, the three-factor models (models 6 to 8 in Tables 2.9 to 2.11) generated a lower average absolute intercept than the two-factor model group (models 2 to 5 in Tables 2.5 to 2.8). Within the two-factor group, model 2 produced the lowest average absolute intercept (0.004 compared with 0.013, 0.011, and 0.011).

Fama and French (2015) also analyzed two ratios in addition to their GRS tests. Therefore, we will also look at these two ratios. As shown in Table 2.13, column 4, the numerator of the first ratio is a measure of the regression's intercept and its denominator is the measure of the dispersion of LHS expected returns. In particular, the A$|a_i|$ is the absolute value of the regressions' intercepts and the A$|\overline{r}_i|$ is the average absolute value of average return on portfolio i minus the average of all portfolio returns. The numerator measures the extent to which the model could not explain the LHS returns. The denominator measures the dispersion of LHS returns to be explained. The lower the ratio, the "better" the model. As we can see, the five-factor model has the lowest ratio (0.60). As a group, the three-factor models (models 6 to 8 in Tables 2.9 to 2.11) have a lower ratio than the two-factor models (models 2 to 5 in Tables 2.5 to 2.8) as a group. Within the two-factor models, model 2 (a two-factor model containing a market and a size factor) has the lowest ratio within the group.

The second ratio in the last column, column 5 of Table 2.13, measures the proportion of the variance of the return of the 16 portfolios left unexplained by the right-hand-side factors. The detail of this ratio can be found on page 10 of

Table 2.13: Summary statistics for tests of one, two-, three- and five-factor model: December 2007 to December 2016. The test scores reveals the ability of the RHS factors as a set explain the LHS monthly excess returns of the 16 mimicking portfolios. The GRS test scores tell to what extent the model regressions' intercepts are jointly zero; the $A|a_i|$ is the absolute value of the intercepts; the first ratios $A|a_i|/A|\bar{r}_i|$ is the average absolute value of intercepts over the average absolute value of $\bar{r}_i$ where $\bar{r}_i$ is the average return on portfolio i minus the average of all portfolio returns; and $A(\hat{\alpha}_i^2)/A(\hat{\mu}_i^2)$ is the $A(\alpha_i^2)/A(\bar{r}_i^2)$ corrected for sampling errors.

	GRS	$A\|a_i\|$	$A\|a_i\|/A\|\bar{r}_i\|$	$A(\hat{\alpha}_i^2)/A(\hat{\mu}_i^2)$
Model 1	3.05	0.013	3.30	-40.40
(CAPM)	p-value: 0.000			
Model 2	2.01	0.004	1.28	-2.52
	p-value 0.020*			
Model 3	3.03	0.013	3.29	-40.31
	p-value 0.000			
Model 4	3.12	0.011	2.69	-27.47
	p-value 0.000			
Model 5	2.77	0.011	2.64	-26.81
	p-value 0.001			
Model 6	1.56	0.003	0.87	-0.15
(FF3)	p-value 0.098**			
Model 7	1.62	0.004	0.98	-0.79
	p-value 0.080**			
Model 8	2.00	0.004	1.27	-2.46
	p-value 0.021*			
Model 9	1.28	0.002	0.60	0.14
(FF5)	p-value 0.229***			

p^{***}>0.10, p^{**}>0.05, p^{*}>0.01

Fama and French (2015). As can be seen, the two-factor models (models 2 to 5 in Tables 2.5 to 2.8) as a group perform better than the CAPM, and the three-factor models (models 6 to 8 in Tables 2.9 to 2.11) as a group perform better than the two-factor models as a group. The five- factor model performs the best among all models examined. Within the two-factor model group, the two- factor model containing a market and a size factor performs the best within the group.

2.5 Conclusions

Among the five factors in the Fama and French five-factor model, the two-factor model containing a market factor and a size factor seems to be the best factor combination to explain the Chinese stock return variations, even though it still does not completely explain those return variations. The GRS tests easily reject all models (except models 6, 7 and 9), while the adjusted R^2s show that over 90% of the stock return variations we studied were explained by this two-factor model.

Our final decision on the two-factor model containing a market and a size factor is based on the following considerations: 1) the regression intercepts, 2) the adjusted R-squared, and 3) the GRS tests. While considering these three regression outcomes, we started by looking at the original simplest CAPM. We then looked at four two-factor models by adding one factor at a time. After that, we looked at three three-factor models containing a market factor and combinations of any two factors amongst the remaining four factors. At the end, we looked at the Fama and French five-factor model.

The biggest improvement in the intercept was found when we added the size factor into the original CAPM. The average absolute value of the intercepts' t-tests dropped dramatically from 2.42 to 1.62. The adjusted R^2 has a similar pattern. The adjusted R^2 improved dramatically from 72% to 93% when we added the size factor into the original CAPM. Finally the GRS test also shows that the biggest improvement appeared when we added the size factor into the CAPM: the GRS score dropped from 3.05 to 2.01.

When comparing all models examined, the Fama and French five-factor model produced the best outcome in terms of the regression intercept, the adjusted R^2s and the GRS test. Yet we still rejected this model for the following three reasons:

Firstly, each of the three factors (HML, CMA and RMW) when considered alone with the market factor, do not seem to have much explanatory power. Secondly, the SMB factor is highly correlated with the HML, the RMW and the CMA factors. Thirdly, it is a fact that the more factors are in a model, the larger the adjusted R^2s. However, we need to consider the marginal cost of adding an extra factor into a model. It was not worthwhile to add extra factors into the model for the amount of R-squared gained.

At the end, it was the decision made between choosing this two-factor model (containing a market and a size factor) and the Fama and French three-factor model (containing a market, a size and a value factor). The focus came down to the fact that the SMB and HML factors are highly negatively correlated, and only one factor between these two should be accepted as a factor. After consideration, we concluded that the B/M ratio was not a reliable ratio in the Chinese stock market (the detailed reasoning is in Section 2.3.1). We decided to discard this HML factor due to its unreliable nature and the fact B/M ratios had a lack of variation. Therefore, our choice of model to explain the Chinese stock variations is the two-factor model containing a market and a size factor (model 2 in Table 2.5).

This result is similar to Hu et al. (2019); Lihui et al. (2014) and Wang and Xu (2004) who all report that only the market and size factors combined best explain Chinese stock return variation. Intentionally, the Brazil market (Rogers and Securato, 2007) also has similar evidence.

3. Sensitivity Analysis

When Fama and French introduced the three- and five-factor models in Fama and French (1993) and Fama and French (2015) respectively, the factors in these models were constructed using previously reported anomalies. In their 2015 study, they explained that these factors could be constructed in different ways, and hence introduced three different factor-construction methods. These are called the 2×3 sort, the 2×2 sort, and the $2 \times 2 \times 2 \times 2$ sort.

The inspiration behind using these alternative factor-construction methods was to test whether the models' performance were sensitive to how the factors were constructed. Although sensitivity analysis in Fama and French (2015) confirmed that the construction methods did not affect model's performance in the US market, we still should test it in China since this market is fundamentally different from that of the US. Therefore, in sensitivity analysis 1, we will test a total of five construction methods, which are somewhat modifications of the original Fama and French 2×3 and 2×2 sorts, to see whether the construction methods indeed do not affect models' performance.

In this study, we not only answer the question of whether the construction methods make any difference to the model's performance, we also answer the question of whether within a specific factor construction method, various breakpoints do make any difference to the models' performance. Therefore, in the second part of this chapter, we conducted a second sensitivity analyses: we focused on one factor construction method to further test whether using different breakpoints will produce statistically different factors.

3.1 Sensitivity Analysis 1: Alternative Factor Constructions

In this section, we perform the sensitivity analysis 1 – testing the five factor-construction methods. The section is designed as follows: Subsection one introduces the original methods introduced in Fama and French (1993) and Fama and French (2015) respectively; Subsection 2 introduce the five methods used in our sensitivity analysis, which are somewhat modifications of the original methods of Fama and French; Subsection three gives factor summary statistics; Subsection four shows the results of the regressions; Subsection five compares the models' performance between the US and China; Subsection six lists all the regression tables; Subsection seven discusses the GRS tests results; and subsection eight gives conclusion on the first sensitivity analysis.

3.1.1 The Fama and French 2×3 and 2×2 Sorts

Before we dive into the five factor-construction methods we developed in this section, we will introduce the original Fama and French 2×3 and 2×2 sorting methods. Note we do not consider the original FF5 $2 \times 2 \times 2 \times 2$ sort, because the Chinese stock market was small, at least at the beginning of our study period [1]. Using the FF5 $2 \times 2 \times 2 \times 2$ sort means we had to split all stocks into 16 intervals according to the total four characteristics (Size, B/M, OP, and Investment). The number of stocks in each of the 16 intervals would be too small to represent stocks

[1] On January 2002, the number of stocks listed on the Shanghai Stock Exchange was only 593.

with those characteristics.

Table 3.1 shows the 2×2 and 2×3 construction methods used in Fama and French (1993) and Fama and French (2015) respectively. Both of the construction methods are aimed at creating sets of factors that are as least correlated as possible. We provide a brief explanation here.

Table 3.1: The original Fama and French (1993, 2015) 2×3 and 2×2 sorting methods. Note we do not consider the original FF5 $2 \times 2 \times 2 \times 2$ sort, because the Chinese stock market was small, at least at the beginning of our study period [2]. Using the FF5 $2 \times 2 \times 2 \times 2$ sort means we had to split all stocks into 16 intervals according to the total four characteristics (Size, B/M, OP, and Investment). The number of stocks in each of the 16 intervals would be too small to represent stocks with those characteristics.

The 1993 FF3 2X3 Construction Method	Size: median points	$SMB = \frac{SL+SN+SH}{3} - \frac{BL+BN+BH}{3}$
	B/M: 30^{th} and 70^{th}	$HML = \frac{HS+HB}{2} - \frac{LS+LB}{2}$
The 2015 FF5 2X3 Construction Method	Size: median points	$SMB_{B/M} = \frac{SL+SN+SH}{3} - \frac{BL+BN+BH}{3}$
		$SMB_{OP} = \frac{SR+SN+SW}{3} - \frac{BR+BN+BW}{3}$
		$SMB_{Inv} = \frac{SC+SN+SA}{3} - \frac{BC+BN+BA}{3}$
		$SMB = \frac{SMB_{B/M}+SMB_{OP}+SMB_{Inv}}{3}$
	B/M: 30^{th} and 70^{th}	$HML = \frac{HS+HB}{2} - \frac{LS+LB}{2}$
	OP: 30^{th} and 70^{th}	$RMW = \frac{RS+RB}{2} - \frac{WS+WB}{2}$
	Inv:30^{th} and 70^{th}	$CMA = \frac{CS+CB}{2} - \frac{AS+AB}{2}$

(*table continued on next page...*)

The 2015 FF5 2X2 Construction Method	Size: median point	$SMB_{B/M} = \frac{SL+SH}{2} - \frac{BL+BH}{2}$
		$SMB_{OP} = \frac{SR+SW}{2} - \frac{BR+BW}{2}$
		$SMB_{Inv} = \frac{SC+SA}{2} - \frac{BC+BA}{2}$
		$SMB = \frac{SMB_{B/M}+SMB_{OP}+SMB_{Inv}}{3}$
	B/M: median point	$HML=\frac{HS+HB}{2} - \frac{LS+LB}{2}$
	OP: median point	$RMW=\frac{RS+RB}{2} - \frac{WS+WB}{2}$
	Inv: median point	$CMA=\frac{CS+CB}{2} - \frac{AS+AB}{2}$

The Fama and French 1993 2×3 **sort** Fama and French in their 1993 study, used *two* variables to calculate average returns of each of the characteristic portfolios. For example, to calculate the SMB factor, they double-sorted all stocks by their two characteristics - size and B/M, and used the resulting six portfolios to calculate the average returns of the small portfolio minus the average returns of the big portfolio. As shown in Table 3.2, the six resulting portfolios are: SL, SN, SH, BL, BN, and BH. The abbreviation SL means portfolio of **small** size and **low** B/M ; the abbreviation SN means portfolio of small size and neutral B/M; the abbreviation SH means portfolio of small size and high B/M; the abbreviation BL means portfolio of big size and low B/M; the abbreviation BN means portfolio of big size and neutral B/M; the abbreviation BH means portfolio of big size and high B/M.

To calculate the size factor, SMB, all stocks were independently sorted on size and B/M. The size variable has *two* intervals (small and big) and the book-to-market variable has *three* intervals (low, neutral, and high). Therefore, it is called a 2×3 sort. This sort created six intervals (the interval portfolio description and abbreviations for this factor construction method are displayed in Table 3.6.): a portfolio containing stocks of small-cap and low B/M (SL); a portfolio containing stocks of small-cap and neutral B/M (SN); a portfolio containing stocks of small-cap and high B/M (SH); a portfolio containing stocks of big market-cap and low B/M portfolio (BL); a portfolio containing stocks of big-cap and neutral B/M (BN); and finally, a portfolio containing stocks of big-cap and high B/M (BH). Then the SMB factor is simply the average return of the three small-capitalization portfolios (SL, SN and SH) minus the average return of the three big-capitalization portfolios (BL, BN, BH). $SMB = \frac{SH+SN+SL}{3} - \frac{BH+BN+BL}{3}$.

For each of the HML, RMW and CMA factors, the market capitalization was used as the second variable to create the double-sorting. The second variable (the market capitalization) was again split into 2 intervals, and the B/M in the HML, the OP in RMW and the investment in the CMA were split into three intervals.

To calculate the HML, we independently double-sorted all stocks by the B/M and the market capitalization. The B/M has three intervals and the size has 2 intervals. Six portfolios were created from this sort: a portfolios containing stocks of high B/M and small-cap (HS); a portfolio containing stocks of high B/M and big-cap (HB); a portfolios containing stocks of neutral B/M and small-cap (NS); a portfolio containing stocks of neutral B/M and big-cap (NB); a portfolio containing stocks of low B/M and small market-cap (LS); and finally, a portfolio containing stocks of low B/M and big market-cap (LB). The HML factor is then the average of the two high B/M portfolios (HS and HB) minus the average return of the two low B/M portfolios (LS and LB). $HML = \frac{HS+HB}{2} - \frac{LS+LB}{2}$.

The Fama and French 2015 2×3 sort The 2×3 sort of 2015 for SMB and HML stayed the same as in 1993. But because there were two more new factors (RMW and CMA), there were more calculations involved.

The calculation of the SMB is in two steps: the first step is to calculate the three partial SMBs using each of the other three variables, namely book-to-market, operating profit and investment style. This step creates three partial size factors: SMB_{BM}, SMB_{OP}, and SMB_{INV} (See Chapter 2 more detailed definitions of the partial factors).

To calculate the first of the three partial size factors, SMB_{BM}, all stocks were independently sorted on size and B/M. The size variable has *two* in-

Table 3.2: Interval portfolio descriptions and abbreviations – Fama and French (1993) 2×3 sort.

Interval Portfolios	**Abbreviations**
Small market cap and **L**ow B/M	SL
Small market cap and **N**eutral book-to-market ratio (B/M)	SN
Small market cap and **H**igh book-to-market ratio (B/M)	SH
Big market cap and **L**ow book-to-market ratio (B/M)	BL
Big market cap and **N**eutral book-to-market ratio	BN
Big market cap and **H**igh book-to-market ratio (B/M)	BH
High book-to-market ratio (B/M) and **S**mall market cap	HS
High book-to-market ratio (B/M) and **B**ig market cap	HB
Neutral book-to-market ratio (B/M) and **S**mall market cap	NS
Neutral book-to-market ratio (B/M) and **B**ig market cap	NB
Low book-to-market ratio (B/M) and **S**mall market cap	LS
Low book-to-market ratio (B/M) and **B**ig market cap	LB

tervals (small and big) and the book-to-market variable has *three* intervals (low, neutral, and high). Therefore, it is called a 2×3 sort. This sort created six intervals (the interval portfolio description and abbreviations for this factor construction method are displayed in Table 3.6.): a portfolio containing stocks of small market-cap and low B/M (SL); a portfolio containing stocks of small market capitalization and neutral B/M (SN); a portfolio containing stocks of small market capitalization and high B/M (SH); a portfolio containing stocks of big market capitalization and low B/M portfolio (BL); a portfolio containing stocks of big market capitalization and neutral B/M (BN); and finally, a portfolio containing stocks of big market capitalization and high B/M (BH). Then the SMB_{BM} partial factor is simply the average return of the three small-capitalization portfolios (SL, SN and SH) minus the average return of the three big-capitalization portfolios (BL, BN, BH). $SMB_{BM} = \frac{SH+SN+SL}{3} - \frac{BH+BN+BL}{3}$. See Table 3.3 for more abbreviations. (See Table 3.3 for the details of the abbreviations.)

To calculate the second of the three partial size factors, SMB_{OP}, all stocks were independently sorted on size and OP. The size variable has *two* intervals (small and big) and the OP variable has *three* intervals (robust, neutral, and weak). This sort created six intervals: a portfolio containing stocks of small market capitalization and robust operating profit (SR); a portfolio containing stocks of small market capitalization and neutral operating profit (SN); a portfolio containing stocks of small market capitalization and weak operating profit (SW); a portfolio containing stocks of big market capitalization and robust operating profit portfolio (BR); a portfolio containing stocks of big market capitalization and neutral operating profit (BN); and finally, a portfolio containing stocks of big market capitalization and weak operating profit (BW). Then the SMB_{OP} partial factor is simply the average return of the three small-capitalization portfolios (SR, SN and SW) minus the average return of the three big-capitalization portfolios (BR, BN, BW). $SMB_{OP} = \frac{SR+SN+SW}{3} - \frac{BR+BN+BW}{3}$.

Similarly, to calculate the last of the three partial size factors, SMB_{Inv}, all stocks were independently sorted on size and investment style. The size variable has *two* intervals (small and big) and the investment style variable has *three* intervals (conservative investment style, neutral investment style, and aggressive investment style). This sort created six intervals: a portfolio containing stocks of small market capitalization and conservative investment style (SC); a portfolio containing stocks of small market capitalization and neutral conservative investment style (SN); a portfolio containing stocks of small market capitalization and aggressive investment style (SA); a portfolio containing stocks of big market capitalization and conservative investment style portfolio (BC); a portfolio containing stocks of big market capitalization and neutral investment style (BN); and finally, a portfolio containing stocks of big market capitalization and aggressive investment style (BA). Then the SMB_{Inv} partial factor is simply the average return of the three small-capitalization portfolios (SC, SN and SA) minus the average return of the three big-capitalization portfolios (BC, BN, BA). $SMB_{Inv} = \frac{SC+SN+SA}{3} - \frac{BC+BN+BA}{3}$.

Now that all the three partial size factors are obtained, the second step is simply calculate the average of the three partial size factors to arrive at the final size factor: $SMB = \frac{SMB_{BM}+SMB_{OP}+SMB_{INV}}{3}$

To calculate the HML, we independently double-sorted all stocks by the B/M and the market capitalization. The B/M has three intervals and the size has two intervals. Six portfolios were created from this sort: a portfolios containing stocks of high B/M and small market capitalization (HS); a portfolio containing stocks of high B/M and big market capitalization (HB); a portfolios containing stocks of neutral B/M and small market capitalization (NS); a portfolio containing stocks of neutral B/M and big market capitalization (NB); a portfolio containing stocks of low B/M and small market capitalization (LS); and finally, a portfolio containing stocks of low B/M and big market capitalization (LB). The HML factor is then the average of the two high B/M portfolios (HS and HB) minus the average return of the two low B/M portfolios (LS and LB). $HML = \frac{HS+HB}{2} - \frac{LS+LB}{2}$.

Same as the rational of the HML, to calculate the RMW, we independently double-sorted all stocks by profitability and market capitalization. The market capitalization was split into two intervals and profitability was split into three intervals. Six portfolios were created from the sort: a portfolio containing stocks of robust profitability and small market capitalization (RS); a portfolio containing stocks of robust profitability and big market capitalization (RB); a portfolio containing stocks of neutral profitability and small market capitalization (NS); a portfolio containing stocks of neutral profitability and big market capitalization (NB); a portfolio containing stocks of weak profitability and small market capitalization (WS); and finally, a portfolio containing stocks of weak profitability and big market capitalization (WB). The RMW factor is then the average return of the two robust profitability portfolios (RS and RB) minus the average return of the two weak profitability portfolios (WS and WB). $RMW = \frac{RS+RB}{2} - \frac{WS+WB}{2}$.

Finally, the CMA factor was calculated using the returns of portfolios with a conservative investment style minus the returns of portfolios with an aggressive investment style. We independently double-sorted all stocks by the investment style and the market capitalization. Within the 2×3 sort, six portfolios were created from the sort: a portfolios containing stocks of conservative investment style and small market capitalization (CS); a portfolio containing stocks of conservative investment style and big market capitalization (CB); a portfolios containing stocks of neutral investment style and small market capitalization (NS); a portfolio containing stocks of neutral investment style and big market capitalization (NB); a portfolio containing stocks of aggressive investment style and small market capitalization (AS); and finally, a portfolio containing stocks of aggressive investment style and big market capitalization (AB). The CMA factor is then the average return of the two conservative investment style portfolios (CS and CB) minus the average return of the two aggressive investment style portfolios (AS and AB). $CMA = \frac{CS+CB}{2} - \frac{AS+AB}{2}$.

The Fama and French 2015 2×2 sort The rational behind the 2×2 sort is similar to the 2×3 sort described earlier. The difference here is that all variables are split into only *two* intervals.

The SMB factor was constructed using all four anomalies namely the size,

Table 3.3: Interval portfolio descriptions and abbreviations – Fama and French (2015) 2×3 sort.

Interval Portfolios	**Abbreviations**
Small market cap and **L**ow B/M	SL
Small market cap and **N**eutral book-to-market ratio (B/M)	SN
Small market cap and **H**igh book-to-market ratio (B/M)	SH
Big market cap and **L**ow book-to-market ratio (B/M)	BL
Big market cap and **N**eutral book-to-market ratio	BN
Big market cap and **H**igh book-to-market ratio (B/M)	BH
Small market cap and **R**obust profitability	SR
Small market cap and **N**eutral profitability	SN
Small market cap and **W**eak profitability	SW
Big market cap and **R**obust profitability	BR
Big market cap and **N**eutral profitability	BN
Big market cap and **W**eak profitability	BW
Small market cap and **A**ggressive investment style	SA
Small market cap and **N**eutral investment style	SN
Small market cap and **C**onservative investment style	SC
Big market cap and **A**ggressive investment style	BA
Big market cap and **N**eutral investment style	BN
Big market cap and **C**onservative investment style	BC
High book-to-market ratio (B/M) and **S**mall market cap	HS
High book-to-market ratio (B/M) and **B**ig market cap	HB
Neutral book-to-market ratio (B/M) and **S**mall market cap	NS
Neutral book-to-market ratio (B/M) and **B**ig market cap	NB
Low book-to-market ratio (B/M) and **S**mall market cap	LS
Low book-to-market ratio (B/M) and **B**ig market cap	LB
Rapid operating profit (OP) and **S**mall market cap	RS
Rapid operating profit (OP) and **B**ig market cap	RB
Neutral operating profit (OP) and **S**mall market cap	NS
Neutral operating profit (OP) and **B**ig market cap	NB
Weak operating profit (OP) and **S**mall market cap	WS
Weak operating profit (OP) and **B**ig market cap	WB
Conservative investment style and **S**mall market cap	CS
Conservative investment style and **B**ig market cap	CB
Neutral investment style and **S**mall market cap	NS
Neutral investment style and **B**ig market cap	NB
Aggressive investment style and **S**mall market cap	AS
Aggressive investment style and **B**ig market cap	AB

book-to-market, profitability and the investment style. The calculation of the SMB is in two steps: the first step is to calculate the three partial SMBs using each of the other three variables, namely book-to-market, operating profit and investment style. This step creates three partial size factors: SMB_{BM}, SMB_{OP}, and SMB_{INV}.

To calculate the three partial size factors, firstly, all stocks were independently sorted on size and B/M. The size was divided into two intervals and the B/M was divided into two intervals (this is why it is called 2×2 sort), which resulted in four interval portfolios (the interval portfolio description and abbreviations for this factor construction method are displayed in Table 3.4): a small market capitalization and low B/M portfolio (SL); and a small market capitalization and high B/M portfolio (SH); a big market capitalization and low book-to market ratio portfolio (BL), a big market capitalization and high B/M portfolio (BH). The SMB_{BM} is then calculated as the average return of the two small cap portfolios minus the average return of the two big market cap portfolios. $SMB_{BM} = \frac{SL+SH}{2} - \frac{BL+BH}{2}$.

Similarly, to calculate the SMB_{OP}, we independently sort all stocks on size and operating profit (therefore a 2×2 sort). This created four portfolios: a small market capitalization and robust operating profit (SR); and a small market capitalization and weak operating profit portfolio (SW); a big market capitalization and robust operating profit portfolio (BR); and a big market capitalization and weak operating profit portfolio (BW). Then the SMB_{OP} is the average return of the two small cap portfolios minus the average return of the two big cap portfolios. $SMB_{OP} = \frac{SR+SW}{2} - \frac{BR+BW}{2}$.

Again, to calculate the SMB_{INV}, we independently sort all stocks on size and investment style (hence a 2×2 sort), which creates four portfolios: a small and aggressive investment style portfolio (SA), and a small and conservative investment style portfolio (SC); a big and aggressive investment style portfolio (BA), and a big and conservative investment style portfolio (BC). Then the SMB_{INV} is the average return of the two small cap portfolios minus the average return of the two big cap portfolios. $SMB_{INV} = \frac{SA+SC}{2} - \frac{BA+BC}{2}$.

Now that all the three partial size factors are obtained, the second step is simply calculate the average return of the three partial size factors to arrive at the final size factor: $SMB = \frac{SMB_{BM}+SMB_{OP}+SMB_{INV}}{3}$.

To calculate the HML, we independently double-sorted all stocks by the B/M and the market capitalization. The B/M has two intervals and the size has two intervals. Four portfolios were created from this sort: a portfolios containing stocks of high B/M and small market capitalization (HS); a portfolio containing stocks of high B/M and big market capitalization (HB); a portfolio containing stocks of low B/M and small market capitalization (LS); and finally, a portfolio containing stocks of low B/M and big market capitalization (LB). The HML factor is then the average of the two high B/M portfolios (HS and HB) minus the average return of the two low B/M portfolios (LS and LB). $HML = \frac{HS+HB}{2} - \frac{LS+LB}{2}$.

Same as the rational of the HML, to calculate the RMW, we independently double-sorted all stocks by the profitability and market capitalization. The market capitalization was split into two intervals and the profitability was split into two intervals. Four portfolios were created from the sort: a portfolio containing stocks of robust profitability and small market capitalization (RS); a portfolio containing stocks of robust profitability and big market capitalization (RB); a portfolio containing stocks of weak profitability and small market capitalization (WS); and finally, a portfolio containing stocks of weak profitability and big market capitalization (WB). The RMW factor is then the average return of the two robust profitability portfolios (RS and RB) minus the average return of the two weak profitability portfolios (WS and WB). $RMW = \frac{RS+RB}{2} - \frac{WS+WB}{2}$.

Finally, the CMA factor was calculated using the returns of portfolios with a conservative investment style minus the returns of portfolios with an aggressive investment style. We independently double-sorted all stocks by the investment style and the market capitalization. Four portfolios were created from the sort: a portfolios containing stocks of conservative investment style and small market capitalization (CS); a portfolio containing stocks of conservative investment style and big market capitalization (CB); a portfolio containing stocks of aggressive investment style and small market capitalization (AS); and finally, a portfolio containing stocks of aggressive investment style and big market capitalization (AB). The CMA factor is then the average return of the two conservative investment style portfolios (CS and CB) minus the average return of the two aggressive investment style portfolios (AS and AB). $CMA = \frac{CS+CB}{2} - \frac{AS+AB}{2}$.

3.1.2 The Five Construction Methods

As described earlier in this study, we tested a total of five difference factor construction methods which are mostly modifications of the original either FF5 2×3 sort or 2×2 sort. These modifications include simplifications or complications of the sorting. In specific, in our first method, SMB was same as the FF3 2×3 sort of 1993, while the other three factors was constructed using FF5 2×3 sort; In our second method, all factors were constructed using FF5 2015 2×2 sort; In our third method, all factors were constructed using all the possible double-sorted portfolios, the same logic used for SMB in the FF5 2015 2×3 sort; In our the fourth factor construction method, all factors were constructed using the FF5

Table 3.4: Interval portfolio descriptions and abbreviations – Fama and French (2015) 2×2 sort.

Interval Portfolios	**Abbreviations**
Small market cap and **L**ow book-to-market ratio (B/M)	SL
Small market cap and **H**igh book-to-market ratio (B/M)	SH
Big market cap and **L**ow book-to-market ratio (B/M)	BL
Big market cap and **H**igh book-to-market ratio (B/M)	BH
Small market cap and **R**obust profitability	SR
Small market cap and **W**eak profitability	SW
Big market cap and **R**obust profitability	BR
Big market cap and **W**eak profitability	BW
Small market cap and **A**ggressive investment style	SA
Small market cap and **C**onservative investment style	SC
Big market cap and **A**ggressive investment style	BA
Big market cap and **C**onservative investment style	BC
High book-to-market ratio (B/M) and **S**mall market cap	HS
High book-to-market ratio (B/M) and **B**ig market cap	HB
Low book-to-market ratio (B/M) and **S**mall market cap	LS
Low book-to-market ratio (B/M) and **B**ig market cap	LB
Rapid operating profit (OP) and **S**mall market cap	RS
Rapid operating profit (OP) and **B**ig market cap	RB
Weak operating profit (OP) and **S**mall market cap	WS
Weak operating profit (OP) and **B**ig market cap	WB
Conservative investment style and **S**mall market cap	CS
Conservative investment style and **B**ig market cap	CB
Aggressive investment style and **S**mall market cap	AS
Aggressive investment style and **B**ig market cap	AB

2015 2×2 sort; and finally, in the fifth method, all the factors were constructed using the same sort as described in the third method, however, the difference is all variables were split into two intervals here.

The data used in this chapter is monthly returns of the A-share stocks listed on the Shanghai Stock Exchange for the period January 2000 to March 2015. The details of these five alternative factor construction methods are listed in Table 3.5. We also provide a brief description below.

Table 3.5: The five factor-construction methods to construct the size, B/M, profitability and investment factors. We independently sort size into two groups, and sort B/M, OP, and investment into two or three groups. Individual factors are then constructed using their value weighted average against different weights and different intervals. Out of the large number of different constructions available, we chose these five to examine whether factor specifics influence models' explanatory power.

Sort	**Break Points Percentile**	**Factors and their components**
Construction method 1	Size: median	$SMB = \frac{SL+SN+SH}{3} - \frac{BL+BN+BH}{3}$
Simplified FF5 2×3 sort	B/M: 30^{th} and 70^{th}	$HML = \frac{HS+HB}{2} - \frac{LS+LB}{2}$
		$RMW = \frac{RS+RB}{2} - \frac{WS+WB}{2}$
		$CMA = \frac{CS+CB}{2} - \frac{AS+AB}{2}$
Construction method 2	Size: median points	$SMB = \frac{1}{3}(\frac{SL+SH}{2} + \frac{SC+SA}{2} + \frac{SR+SW}{2})$
Simplified FF5 2×3 sort	B/M:30^{th} and 70^{th}	$-\frac{1}{3}(\frac{BL+BH}{2} + \frac{BC+BA}{2} + \frac{BR+BW}{2})$
		$HML = \frac{HS+HB}{2} - \frac{LS+LB}{2}$
		$RMW = \frac{RS+RB}{2} - \frac{WS+WB}{2}$
		$CMA = \frac{CS+CB}{2} - \frac{AS+AB}{2}$

(*table continued on next page...*)

Construction method 3	Size: median points	$SMB=\frac{1}{3}(\frac{SL+SN+SH}{3}+\frac{SC+SN+SA}{3}+\frac{SR+SN+SW}{3})$
Complicated FF5 2×3 sort		$-\frac{1}{3}(\frac{BL+BN+BH}{3}+\frac{BC+BN+BA}{3}+\frac{BR+BN+BW}{3})$
	B/M: 30$^{\text{th}}$ and 70$^{\text{th}}$	$HML=\frac{1}{3}(\frac{HS+HB}{2}+\frac{HC+HN+HA}{3}+\frac{HR+HN+HW}{3})$
		$-\frac{1}{3}(\frac{LS+LB}{2}+\frac{LC+LN+LA}{3}+\frac{LR+LN+LW}{3})$
	Inv:30$^{\text{th}}$ and 70$^{\text{th}}$	$RMW=\frac{1}{3}(\frac{RS+RB}{2}+\frac{RH+RN+RL}{3}+\frac{RC+RN+RW}{3})$
		$-\frac{1}{3}(\frac{AS+AB}{3}+\frac{AH+AN+AL}{3}+\frac{AR+BN+AW}{3})$
	OP: 30$^{\text{th}}$ and 70$^{\text{th}}$	$CMA=\frac{1}{3}(\frac{VS+CB}{2}+\frac{CH+CN+CL}{3}+\frac{CR+CN+CW}{3})$
		$-\frac{1}{3}(\frac{WS+WB}{2}+\frac{WH+WN+WL}{3}+\frac{WC+WN+WA}{3})$
Construction method 4	Size: median point	$SMB=\frac{SL+SH}{2}-\frac{BL+BH}{2}$
FF5 2×2 sort	B/M: median point	$HML=\frac{HS+HB}{2}-\frac{LS+LB}{2}$
	OP: median point	$RMW=\frac{RS+RB}{2}-\frac{WS+WB}{2}$
	Inv: median point	$CMA=\frac{CS+CB}{2}-\frac{AS+AB}{2}$

(*table continued on next page...*)

Construction method 5	Size: median	$SMB = \frac{1}{3}(\frac{SL+SH}{2} + \frac{SC+SA}{2} + \frac{SR+SW}{2})$
Complicated FF5 2×2 sort		$-\frac{1}{3}(\frac{BL+BH}{2} + \frac{BC+BA}{2} + \frac{BR+BW}{2})$
	B/M: median	$HML = \frac{1}{3}(\frac{HS+HB}{2} + \frac{HC+HA}{2} + \frac{HR+HW}{2})$
		$-\frac{1}{3}(\frac{LS+LB}{2} + \frac{LC+LA}{2} + \frac{LR+LW}{2})$
	Inv: median	$RMW = \frac{1}{3}(\frac{RS+RB}{2} + \frac{RH+RL}{2} + \frac{RC+RW}{2})$
		$-\frac{1}{3}(\frac{AS+AB}{2} + \frac{AH+AL}{2} + \frac{AR+AW}{2})$
	OP: median	$CMA = \frac{1}{3}(\frac{CS+CB}{2} + \frac{CH+CL}{2} + \frac{CR+CW}{2})$
		$-\frac{1}{3}(\frac{WS+WB}{2} + \frac{WH+WL}{2} + \frac{WC+WA}{2})$

Construction Method 1: The first method of factor construction is the simplest one among all. In this method, we used two variables to calculate the average returns of each of the characteristic portfolios. For example, to calculate the SMB factor, we double-sorted all portfolios by the two variables – size and B/M – and used the four portfolios defined by these two variables (for example, small and low B/M ratio) to find the average returns of the small portfolio minus the average returns of the big portfolio.

To calculate the SMB factor, we double-sorted all stocks independently by size (market capitalization) and B/M simultaneously. The size variable has two intervals (small and big) and the book-to-market variable has three intervals (low, neutral and high); therefore, it is called a 2×3 sort. This sort created six intervals or portfolios (the interval portfolio description and abbreviations for this factor construction method are displayed in Table 3.6.): a portfolio containing stocks of small market capitalization and low B/M (SL); a portfolio containing stocks of small market capitalization and neutral B/M (SN); a portfolio containing stocks of small market capitalization and high B/M (SH); a portfolio containing stocks of big market capitalization and low B/M portfolio (BL); a portfolio containing stocks of big market capitalization and neutral B/M (BN); and finally, a portfolio containing stocks of big market capitalization and high B/M (BH). Then the SMB factor is simply the average return of the three small-capitalization portfolios (SL, SN and SH) minus the average return of the three big-capitalization portfolios (BL, BN and BH). $SMB = \frac{SH+SN+SL}{3} - \frac{BH+BN+BL}{3}$. This construction is also described in the formula in Table 3.5 (Construction method 1).

For each of the HML, RMW and CMA factors, the market capitalization was used as the second variable to make the double-sort. For each of the three factors, both variables used were split into two intervals, therefore they (the HML, RMW, and CMA) are all 2×2 sorts. For example, to calculate the HML, we independently double-sorted all stocks by the B/M and the market capitalization. The B/M has two intervals and the size has two intervals. Four portfolios were created from this sort: a portfolios containing stocks of high B/M and small market capitalization (HS); a portfolio containing stocks of high B/M and big market capitalization (HB); a portfolio containing stocks of low B/M and small market capitalization (LS); and finally, a portfolio containing stocks of low B/M and big market capitalization (LB). The HML factor is then the average return of the two high B/M portfolios (HS and HB) minus the average return of the two low B/M portfolios (LS and LB). $HML = \frac{HS+HB}{2} - \frac{LS+LB}{2}$.

The third factor to construct is the RMW factor. This factor represents firms' profitability; in particular, it is **r**obust profitability minus **w**eak profitability. The detailed construction of this factor is described in Section 2.1. Again, to calculate the RMW, we independently double-sorted all stocks by the profitability and market capitalization. Therefore, again, within the 2×2 sort, four portfolios were created from the sort: a portfolios containing stocks of robust profitability and small market capitalization (RS); a portfolio containing stocks of robust profitability and big market capitalization (RB); a portfolio containing stocks of weak profitability and small market capitalization (WS); and finally, a portfolio containing stocks of weak profitability and big market capitalization (WB). The RMW factor is then the average return of the two robust profitability portfolios (RS and RB) minus the average return of the two weak profitability portfolios (WS and WB). $RMW = \frac{RS+RB}{2} - \frac{WS+WB}{2}$.

Finally, we calculated the CMA which represents the firms' investment-style. This factor is calculated using the returns of portfolios with a **c**onservative investment style minus the returns of portfolios with an **a**ggressive investment style. See more detailed description of this factor in Section 2.1. We independently double-sorted all stocks by the investment style and the market capitalization. Within the 2×2 sort, four portfolios were created from the sort: a portfolios containing stocks of a conservative investment style and small market capitalization (CS); a portfolio containing stocks of a conservative investment style and big market capitalization (CB); a portfolio containing stocks of an aggressive investment style and small market capitalization (AS); and finally, a portfolio containing stocks of an aggressive investment style and big market capitalization (AB). The CMA factor is then the average return of the two conservative investment style portfolios (CS and CB) minus the average return of the two aggressive investment style portfolios (AS and AB). $CMA = \frac{CS+CB}{2} - \frac{AS+AB}{2}$.

Construction Method 2: This method uses only two intervals to split the other variable in the calculation of the partial size factor (SMB_{BM}, SMB_{OP} and SMB_{INV}). The sort type for the size factor is a $2 \times 2 \times 2 \times 2$ sort (variables are split into two intervals and four variables were used in the calculation). In other words, the four variables in the $2 \times 2 \times 2 \times 2$ sort represent the four variables respectively; they are size, B/M, profitability and investment-style. The value of the variables (in this case is "2" for each variable) represents the number of intervals the variables were split into. The first "2" means the size variable was split into two intervals (small and big); the second "2" means the B/M was split into two intervals (high and low); the third "2" means the profitability was split into two intervals (robust and weak); and finally, the last "2" means the investment-style was split into two intervals (conservative and aggressive).

Table 3.6: Interval portfolio descriptions and abbreviations – Method 1.

Interval Portfolios	**Abbreviations**
Small market cap and **L**ow B/M	SL
Small market cap and **N**eutral book-to-market ratio (B/M)	SN
Small market cap and **H**igh book-to-market ratio (B/M)	SH
Big market cap and **L**ow book-to-market ratio (B/M)	BL
Big market cap and **N**eutral book-to-market ratio	BN
Big market cap and **H**igh book-to-market ratio (B/M)	BH
High book-to-market ratio (B/M) and **S**mall market cap	HS
High book-to-market ratio (B/M) and **B**ig market cap	HB
Low book-to-market ratio (B/M) and **S**mall market cap	LS
Low book-to-market ratio (B/M) and **B**ig market cap	LB
Robust profitability and **S**mall market cap	RS
Robust profitability and **B**ig market cap	RB
Weak profitability and **S**mall market cap	WS
Weak profitability and **B**ig market cap	WB
Conservative investment style and **S**mall market cap	CS
Conservative investment style and **B**ig market cap	CB
Aggressive profitability and **S**mall market cap	AS
Aggressive profitability and **B**ig market cap	AB

The calculation of the SMB is in two steps: the first step is to calculate the three partial SMBs using each of the other three variables, namely book-to-market, operating profit and investment style. This step creates three partial size factors: SMB_{BM}, SMB_{OP}, and SMB_{INV} (see Chapter 2 for more detailed definitions of the partial factors).

To calculate the three partial size factors, firstly, all stocks were independently sorted on size and B/M. The size was divided into two intervals and the B/M was also divided into two intervals, which resulted in four portfolios (the interval portfolio description and abbreviations for this factor construction method are displayed in Table 3.7.): a small market capitalization and low B/M portfolio (SL); and a small market capitalization and high B/M portfolio (SH); a big market capitalization and low book-to market ratio portfolio (BL); and a big market capitalization and high B/M portfolio (BH). The SMB_{BM} was then calculated as the average return of the two small-cap portfolios minus the average return of the two big-cap portfolios. $SMB_{BM} = \frac{SL+SH}{2} - \frac{BL+BH}{2}$. Similarly, to calculate the SMB_{OP}, we independently sorted all stocks on size and operating profit, which created four portfolios: a small market capitalization and robust operating profit (SR); and a small market capitalization and weak operating profit portfolio (SW); a big market capitalization and robust operating profit portfolio (BR); and a big market capitalization and weak operating profit portfolio (BW). Then the SMB_{OP} is the average return of the two small-cap portfolios minus the average return of the two big-cap portfolios. $SMB_{OP} = \frac{SR+SW}{2} - \frac{BR+BW}{2}$. Again, to calculate the SMB_{INV}, we independently sort all stocks on size and investment style, which creates four portfolios: a small and aggressive investment style portfolio (SA) and a small and conservative investment style portfolio (SC); a big and aggres-

Table 3.7: Interval portfolio descriptions and abbreviations – Method 2.

Interval Portfolios	**Abbreviations**
Small market cap and **L**ow book-to-market ratio (B/M)	SL
Small market cap and **H**igh book-to-market ratio (B/M)	SH
Big market cap and **L**ow book-to-market ratio (B/M)	BL
Big market cap and **H**igh book-to-market ratio (B/M)	BH
Small market cap and **R**obust profitability	SR
Small market cap and **W**eak profitability	SW
Big market cap and **R**obust profitability	BR
Big market cap and **W**eak profitability	BW
Small market cap and **A**ggressive investment style	SA
Small market cap and **C**onservative investment style	SC
Big market cap and **A**ggressive investment style	BA
Big market cap and **C**onservative investment style	BC

sive investment style portfolio (BA), and a big and conservative investment style portfolio (BC). Then the SMB_{INV} is the average return of the two small cap portfolios minus the average return of the two big cap portfolios. $SMB_{INV} = \frac{SA+SC}{2} - \frac{BA+BC}{2}$.

Now that all the three partial size factors are obtained, the second step is to simply calculate the average of the three partial size factors to arrive at the final size factor: $SMB = \frac{SMB_{BM}+SMB_{OP}+SMB_{INV}}{3}$

Note that the other three factors, HML, RMW and CMA, are constructed the same way as in construction method 1. They are not described in detail again here but are listed in construction method 2 in Table 3.5.

Construction Method 3: This method is the most complicated method out of the all five methods. The SMB factor was constructed using all four anomalies, namely the size, book-to-market, profitability and the investment style. The method is exactly the same as the 2×3 sort described in Fama and French (2015) in Table 3, page 6. For consistency, we call the sorting for the SMB factor a $2 \times 3 \times 3 \times 3$, which implies in the process of calculating the SMB factor, all four variables were used and they each were split into 2, 3, 3, and 3 intervals. In other words, the four variables in the $2 \times 3 \times 3 \times 3$ sort represent the four variables respectively; they are size, B/M, profitability and investment-style. The value of the variables (in this case 2 and 3) represent the number of intervals the variables were split into. The first variable "2" means the size variable was split into two intervals (small and big); the second variable "3" means the B/M was split into three intervals (high, neutral and low); the third variable "3" means the profitability was split into three intervals (robust, neutral and weak); and finally, the last variable "3" means the investment-style was split into three intervals (conservative, neutral and aggressive).

The calculation of the SMB is in two steps: the first step is to calculate the three partial SMBs using each of the other three variables, namely book-to-market, operating profit and investment style. This step creates three partial size factors: SMB_{BM}, SMB_{OP}, and SMB_{INV}.

To calculate the three partial size factors, firstly, all stocks were independently sorted on size and B/M. The size was divided into two intervals and the B/M was divided into three intervals (2×3 sort), which resulted in six mimicking portfolios (the interval portfolio description and abbreviations for this factor construction method are displayed in Table 3.8): a small market capitalization and low B/M portfolio (SL); a small market capitalization and neutral B/M portfolio (SN); and a small market-cap and high B/M portfolio (SH); a big market-cap and low book-to-market ratio portfolio (BL), a big market capitalization and neutral B/M portfolio (SN); and a big-cap and high B/M portfolio (BH). The SMB_{BM} is then calculated as the average return of the three small cap portfolios minus the average return of the three big market cap portfolios. $SMB_{BM} = \frac{SL+SN+SH}{3} - \frac{BL+BN+BH}{3}$.

Similarly, to calculate the SMB_{OP}, we independently sort all stocks on size and operating profit (2×3 sort). This created six mimicking portfolios: a small market capitalization and robust operating profit (SR); a small market capitalization and neutral operating profit (SN), and a small market capitalization and weak operating profit portfolio (SW); a big market-cap and robust operating profit portfolio (BR); a big-cap and neutral operating profit (SN); and a big market capitalization and weak operating profit portfolio (BW). Then the SMB_{OP} is the average return of the three small-cap portfolios minus the average return of the three big-cap portfolios. $SMB_{OP} = \frac{SR+SN+SW}{3} - \frac{BR+BN+BW}{3}$.

Again, to calculate the SMB_{INV}, we independently sort all stocks on size and investment style (2×3 sort), which creates six mimicking portfolios: a small and aggressive investment style portfolio (SA); a small and neutral investment style portfolio (SN), a small and conservative investment style portfolio (SC), a big and aggressive investment style portfolio (BA); a big and neutral investment style portfolio (BN), and a big and conservative investment style portfolio (BC). Then the SMB_{INV} is the average return of the three small cap portfolios minus the average return of the three big cap portfolios. $SMB_{INV} = \frac{SA+SN+SC}{3} - \frac{BA+BN+BC}{3}$.

Now that all the three partial size factors are obtained, the second step is simply calculate the average return of the three partial size factors to arrive at the final size factor: $SMB = \frac{SMB_{BM}+SMB_{OP}+SMB_{INV}}{3}$.

The sorting used in calculating the HML factor is called the $2\times2\times3\times3$ sort. We calculate the HML factor in two steps. The first step is to calculate the three partial HMLs using each of the other three variables, namely market capitalization, operating profit and investment style. This step creates three partial HML factors: HML_{Size}, HML_{OP}, and HML_{INV}. We double-sorted all stocks independently by size (market capitalization) and B/M (2×2 sort). This sort created four intervals or portfolios: a portfolio containing stocks of high B/M and small market capitalization (HS); a portfolio containing stocks of high B/M and big market capitalization (HB); a portfolio containing stocks of low B/M and small market capitalization (LS); a portfolio containing stocks of low B/M and big market capitalization (LB). The HML_{Size} is then the average return of the two high book-to-market portfolios minus the average return of the two low book-to-market portfolios. $HML_{Size} = \frac{HS+HB}{2} - \frac{LS+LB}{2}$

To calculate the HML_{OP}, we double-sorted all stocks independently by B/M and operating profit level (2×2 sort). This sort created four intervals or portfolios: a portfolio containing stocks of high B/M and robust operating profit (HR); a portfolio containing stocks of high B/M and weak operating profit (HW); a portfolio containing stocks of low B/M and robust operating profit (LR); and a portfolio containing stocks of low B/M and weak operating profit (LW). The HML_{OP} is then the average return of the two high B/M portfolios minus the average return of the two low B/M portfolios. $HML_{OP} = \frac{HR+HW}{2} - \frac{LR+LW}{2}$

Finally, to calculate the HML_{INV}, we double-sorted all stocks independently by B/M and investment style level (2×2 sort). This sort created four intervals or portfolios: a portfolio containing stocks of high B/M and conservative investment style (HC); a portfolio containing stocks of high B/M and aggressive investment style (HA); a portfolio containing stocks of low B/M and conservative investment style (LC); and a portfolio containing stocks of low B/M and aggressive investment style (LA). The HML_{INV} is

Table 3.8: Interval portfolio descriptions and abbreviations – Method 3.

Interval Portfolios	**Abbreviations**
Small market cap and **L**ow book-to-market ratio (B/M)	SL
Small market cap and **N**eutral book-to-market ratio (B/M)	SN
Small market cap and **H**igh book-to-market ratio (B/M)	SH
Big market cap and **L**ow book-to-market ratio (B/M)	BL
Big market cap and **N**eutral book-to-market ratio (B/M)	BN
Big market cap and **H**igh book-to-market ratio (B/M)	BH
High book-to-market ratio (B/M) and **R**obust profitability	HR
High book-to-market ratio (B/M) and **W**eak profitability	HW
Low book-to-market ratio (B/M) and **R**obust profitability	LR
Low book-to-market ratio (B/M) and **W**eak profitability	LW
High book-to-market ratio (B/M) and **C**onservative investment style	HC
High book-to-market ratio (B/M) and **A**ggressive investment style	HA
Low book-to-market ratio (B/M) and **C**onservative investment style	LC
Low book-to-market ratio (B/M) and **A**ggressive investment style	LA

then the average return of the two high B/M portfolios minus the average return of the two low B/M portfolios. $HML_{INV} = \frac{HC+HA}{2} - \frac{LC+LA}{2}$

Now that all the three partial book-to-market factors are obtained, the second step is to simply calculate the average return of the three partial book-to-market factors to arrive the final HML: $HML = \frac{HML_{Size}+HML_{OP}+HML_{INV}}{3}$

This construction is also shown in Table 3.5.

Construction Method 4: This method is the simplest method in terms of calculation. To create the size factor, all stocks were independently double-sorted on size and B/M ratio (2 × 2 sort). The breakpoint for size is the median point of all stocks and the breakpoint for B/M is the median point for all B/M ratios. The sort created four portfolios (the interval portfolio description and abbreviations for the construction of the size factor in method 4 are displayed in Table 3.9.): small and low (SL), small and high (SH), big and low (BL) and big and high (BH). Finally, the SMB factor is the average return of the two small portfolios (SL+SH) minus the average

Table 3.9: Interval portfolio descriptions and abbreviations – Method 4.

Interval Portfolios	**Abbreviations**
Small market cap and **L**ow book-to-market ratio (B/M)	SL
Small market cap and **H**igh book-to-market ratio (B/M)	SH
Big market cap and **L**ow book-to-market ratio (B/M)	BL
Big market cap and **H**igh book-to-market ratio (B/M)	BH
Small market cap and **R**obust profitability	SR
Small market cap and **W**eak profitability	SW
Big market cap and **R**obust profitability	BR
Big market cap and **W**eak profitability	BW
Small market cap and **A**ggressive investment style	SA
Small market cap and **C**onservative investment style	SC
Big market cap and **A**ggressive investment style	BA
Big market cap and **C**onservative investment style	BC

return of the big portfolios (BL+BH). $SMB = \frac{SL+SH}{2} - \frac{BL+BH}{2}$.

The HML, RMW and CMA factors in this methods are calculated in the exactly the same way as they are in method 1 (see more detailed definition in Section 2.1 of Chapter 2).

Construction Method 5: Under this method, the SMB is constructed exactly the same as in method 2. The HML, RMW and CMA factors are constructed in the same way as they are in construction method 3. Therefore, they will not be described again here.

3.1.3 Factor Summary Statistics

The summary statistics for factors constructed using all five methods are reported in Tables 3.10 to 3.14.

As shown in panel A of all tables, SMB and HML were the two factors that may explain stock return variation in the China's Shanghai and Shenzhen stock exchanges. The standard deviations of SMB and HML ranged from 4.80 to 7.60 and 3.77 to 4.88, respectively, and the t-statistics ranged from 1.63 to 2.13, and 1.53 to 2.98, respectively. The mean of the market excess returns was -0.03%, with a t-statistics of -0.04. The mean of SMB ranged from 0.53% to 1.02% and the mean of HML ranged from 0.53% to 0.61% for all construction methods. The standard deviation and the t-statistics for RMW ranged from 3.18 to 4.78 and 0.04 to 1.57 for all construction methods and the standard deviation and t-statistics for CMA ranged from 2.36 to 3.03 and -1.69 to -0.09.

Panel B of Tables 3.10 to Table 3.14 show the correlations between the different factors of each construction method. All tables show that SMB was highly correlated with HML and RMW. The correlation between SMB and HML ranged from -0.47 (in Table 3.14) to -0.35 (in Table 3.10) and the correlation between SMB and RMW range from -0.87 (in Table 3.14) to -0.75 (in Table 3.13).

Table 3.10: Summary statistics for the factors constructed under construction method 1. Panel A displays the mean, standard deviation, and t-statistics for the four factors: SMB, HML, RMW, and CMA. Panel A also displays the value premium, profitability premium and investment style premium for small and big stocks. Panel B displays the correlation among the five factors including the market factor, SMB, HML, RMW and CMA.

Panel A: Mean, standard deviations, and t-tests of monthly returns

Factors from method 1

	$R_M - R_F$	SMB	HML	RMW	CMA
Mean	-0.03	0.76	0.60	0.32	-0.22
std dev.	8.53	5.86	3.77	3.67	2.36
t-Statistics	-0.04	1.68	2.07	1.11	-1.22

	HML_S	HML_B	HML_{S-B}
Mean	0.42	0.78	-0.36
std dev.	2.64	6.12	5.67
t-Statistics	2.07	1.65	-0.82
	RMW_S	RMW_B	RMW_{S-B}
Mean	0.30	0.33	-0.03
std dev.	2.82	6.04	5.90
t-Statistics	1.38	0.71	-0.07
	CMA_S	CMA_B	CMA_{S-B}
Mean	-0.01	-0.43	0.42
std dev.	1.53	4.52	4.82
t-Statistics	-0.09	-1.25	1.14

Panel B: Correlation between different factors.

	$R_M - R_F$	SMB	HML	RMW	CMA
$R_M - R_F$	1.00	0.17	-0.08	-0.13	-0.04
SMB		1.00	-0.35	-0.77	0.12
HML			1.00	0.29	0.14
RMW				1.00	-0.16
CMA					1.00

Table 3.11: Summary statistics for the factors constructed under construction method 2. Panel A displays the mean, standard deviation, and t-statistics for the four factors: SMB, HML, RMW, and CMA. Panel A also displays the value premium, profitability premium and investment style premium for small and big stocks. Panel B displays the correlation among the five factors including the market factor, SMB, HML, RMW and CMA.

Panel A: Mean, standard deviations, and t-tests of monthly returns

Factors from method 2

	$R_M - R_F$	SMB	HML	RMW	CMA
Mean	-0.03	0.67	0.53	0.27	-0.10
std dev.	8.53	4.80	3.89	3.73	2.74
t-Statistics	-0.04	1.81	1.78	0.92	-0.49

	HML_S	HML_B	HML_{S-B}
Mean	0.40	0.67	-0.27
std dev.	2.60	6.47	6.05
t-Statistics	1.99	1.34	-0.58
	RMW_S	RMW_B	RMW_{S-B}
Mean	0.41	0.13	0.28
std dev.	2.93	6.12	6.04
t-Statistics	1.80	0.27	0.60
	CMA_S	CMA_B	CMA_{S-B}
Mean	-0.00	-0.20	0.20
std dev.	1.57	5.08	5.14
t-Statistics	-0.03	-0.52	0.50

Panel B: Correlation between different factors.

	$R_M - R_F$	SMB	HML	RMW	CMA
$R_M - R_F$	1.00	-0.05	-0.14	-0.23	0.18
SMB		1.00	-0.43	-0.76	0.48
HML			1.00	0.37	-0.24
RMW				1.00	-0.44
CMA					1.00

Table 3.12: Summary statistics for the factors constructed under construction method 3. Panel A displays the mean, standard deviation, and t-statistics for the four factors: SMB, HML, RMW, and CMA. Panel A also displays the value premium, profitability premium and investment style premium for small and big stocks. Panel B displays the correlation among the five factors including the market factor, SMB, HML, RMW and CMA.

Panel A: Mean, standard deviations, and t-tests of monthly returns

Factors from method 3

	$R_M - R_F$	SMB	HML	RMW	CMA
Mean	-0.03	1.02	0.58	0.01	-0.02
std dev.	8.53	7.60	4.88	4.78	3.03
t-Statistics	-0.04	1.74	1.53	0.04	-0.09

	HML_S	HML_B	HML_{S-B}
Mean	0.40	0.67	-0.27
std dev.	2.60	6.47	6.05
t-Statistics	1.99	1.34	-0.58
	RMW_S	RMW_B	RMW_{S-B}
Mean	0.41	0.13	0.28
std dev.	2.93	6.12	6.04
t-Statistics	1.80	0.27	0.60
	CMA_S	CMA_B	CMA_{S-B}
Mean	-0.01	-0.24	0.23
std dev.	1.44	5.17	5.14
t-Statistics	-0.13	-0.85	0.81

Panel B: Correlation between different factors.

	$R_M - R_F$	SMB	HML	RMW	CMA
$R_M - R_F$	1.00	-0.03	-0.19	-0.22	0.14
SMB		1.00	-0.42	-0.86	0.55
HML			1.00	0.38	-0.22
RMW				1.00	-0.47
CMA					1.00

Table 3.13: Summary statistics for the factors constructed under construction method 4. Panel A displays the mean, standard deviation, and t-statistics for the four factors: SMB, HML, RMW, and CMA. Panel A also displays the value premium, profitability premium and investment style premium for small and big stocks. Panel B displays the correlation among the five factors including the market factor, SMB, HML, RMW and CMA.

Panel A: Mean, standard deviations, and t-tests of monthly returns

Factors from method 4

	$R_M - R_F$	SMB	HML	RMW	CMA
Mean	-0.03	0.67	0.61	0.31	-0.22
std dev.	8.53	5.79	3.79	3.67	2.39
t-Statistics	-0.04	2.13	2.98	1.57	-1.69

	HML_S	HML_B	HML_{S-B}
Mean	0.42	0.78	-0.33
std dev.	2.64	6.12	5.56
t-Statistics	2.07	2.33	-1.09
	RMW_S	RMW_B	RMW_{S-B}
Mean	0.28	0.34	-0.06
std dev.	2.76	6.02	5.83
t-Statistics	1.89	1.05	-0.19
	CMA_S	CMA_B	CMA_{S-B}
Mean	0.01	-0.45	0.46
std dev.	1.50	4.55	4.80
t-Statistics	0.11	-1.82	1.76

Panel B: Correlation between different factors.

	$R_M - R_F$	SMB	HML	RMW	CMA
$R_M - R_F$	1.00	0.22	-0.08	-0.13	-0.04
SMB		1.00	-0.38	-0.75	0.10
HML			1.00	0.29	0.14
RMW				1.00	-0.16
CMA					1.00

Table 3.14: Summary statistics for the factors constructed under construction method 5. Panel A displays the mean, standard deviation, and t-statistics for the four factors: SMB, HML, RMW, and CMA. Panel A also displays the value premium, profitability premium and investment style premium for small and big stocks. Panel B displays the correlation among the five factors including the market factor, SMB, HML, RMW and CMA.

Panel A: Mean, standard deviations, and t-tests of monthly returns					
Factors from method 5					
	$R_M - R_F$	SMB	HML	RMW	CMA
Mean	-0.03	0.70	0.61	0.05	-0.04
std dev.	8.53	5.56	4.68	4.64	2.70
t-Statistics	-0.04	1.63	1.70	0.14	-0.20
	HML_S	HML_B	HML_{S-B}		
Mean	0.40	0.67	-0.27		
std dev.	2.60	6.47	6.05		
t-Statistics	1.99	1.34	-0.58		
	RMW_S	RMW_B	RMW_{S-B}		
Mean	0.41	0.13	0.28		
std dev.	2.93	6.12	6.04		
t-Statistics	1.80	0.27	0.60		
	CMA_S	CMA_B	CMA_{S-B}		
Mean	-0.00	-0.20	0.20		
std dev.	1.57	5.08	5.14		
t-Statistics	-0.03	-0.52	0.50		
Panel B: Correlation between different factors.					
	$R_M - R_F$	SMB	HML	RMW	CMA
$R_M - R_F$	1.00	0.14	-0.14	-0.23	0.11
SMB		1.00	-0.47	-0.87	0.50
HML			1.00	0.35	-0.18
RMW				1.00	-0.42
CMA					1.00

Table 3.15: Correlation between SMB factors of different constructions.

	$SMB1$	$SMB2$	$SMB3$	$SMB4$	$SMB5$
$SMB1$	1.00	0.97	0.98	0.97	0.99
$SMB2$		1.00	0.99	0.94	0.98
$SMB3$			1.00	0.94	0.98
$SMB4$				1.00	0.98
$SMB5$					1.00

Table 3.16: Correlation between HML factors of different constructions.

	HML1	HML2	HML3	HML4	HML5
HML1	1.00	0.98	0.95	1.00	0.95
HML2		1.00	0.97	0.98	0.97
HML3			1.00	0.95	0.99
HML4				1.00	0.95
HML5					1.00

The last set of comparative tables are Tables 3.15 to 3.18 where correlations between different constructions of the same factor are compared. As can be seen in Tables 3.15 to 3.18, except for the CMA factor, all factors have high correlations with their alternatives. For example, in Table 3.15, the five versions of SMBs constructed using the five different construction methods produced similar SMB factors. The correlation among the five versions of factors ranged from 0.94 to 1.

The factor that showed a slightly different result is the CMA factor. As shown in Table 3.18, the five versions of the CMA factor constructed using the five different methods have a slightly lower correlations than indicated for the other factors. For example, the correlation between CMA1 and CMA2 is only 0.53, which indicates the two construction methods produced two fundamentally different factors. With the limited data and time available, we are not able to study further why this difference took place. But this is a great future research question.

Table 3.17: Correlation between RMW factors of different constructions.

	RMW1	RMW2	RMB3	RMW4	RMW5
RMW1	1.00	0.91	0.90	1.00	0.89
RMW2		1.00	0.98	0.91	0.96
RMW3			1.00	0.90	0.99
RMW4				1.00	0.89
RMW5					1.00

Table 3.18: Correlation between CMA factors of different constructions.

	CMA1	CMA2	CMA3	CMA4	CMA5
CMA1	1.00	0.53	0.59	1.00	0.65
CMA2		1.00	0.95	0.53	0.86
CMA3			1.00	0.59	0.95
CMA4				1.00	0.65
CMA5					1.00

3.1.4 The Regressions Results

We now move to the more important section of testing how well the two-, three- and five-factor models explain the stock return variations in the China's Shanghai and Shenzhen stock markets using the ordinary least squares (OLS) regression. To test whether a multi-factor model is powerful at capturing stock return variations, we look at two aspects: 1) whether we can reject the null hypothesis that the intercepts are jointly zero (see Section 2.4.2 of Chapter 2 for a similar discussion), and 2) whether each factor in the model has high explanatory power in the linear regression judged by the adjusted R^2s. For the aspect 1), we use the GRS test. A GRS test is a joint F-test that tests the null hypothesis whether variables (in our case, the intercepts generated by the regressions) are jointly zero. A high p-value or a low GRS test score would indicate that the test rejects the alternative hypothesis that they are not jointly zero, in other words, accept the null hypothesis that the variables are jointly zero. This is a result we expect for a successful multi-factor model. As for the aspect 2), we expect high adjusted-R^2s for a powerful multi-factor model.

Except generating a set of intercepts and adjusted- R^2s, the running of the regressions would result in a set of other figures including the βs for the factors. The only β that has an expected value is the β for the market factor suggested by the CAPM. We do not have expected value for βs of the rest of the factors. But instead, we will analyze the magnitude and the signs of the other βs to get some insights on stock returns' behaviour suggested by our model.

For completeness, in addition to examining our optimal two-factor model found in Chapter 2, we also examine the Fama and French three- and five-factor models. Therefore, there are three models to be examined. Within each model, we examine five sets of factors constructed using the five construction methods.

Hence, the total number of regressions is 15, and they are displayed in Tables 3.19 to 3.33.

In Chapter 2, we focused on determining, comparatively, the set of factors that best explain the Chinese stock return variations. Given that the best set of factors we found was the two-factors model containing a market factor and a size factor, the natural focus for the regression analysis should be this two-factor model. However, since the Fama and French three- and five- factor models are still more popular than our model, we will include the three- and five-factor model in this regression analysis. Therefore, there will be a total of three models. Because we have a total of five constructions for each model, the total number of regressions below is therefore 15.

The regression analyses are described in Tables 3.19 to 3.33.

The two-factor model regression is

$$R_{i,t} - R_{f,t} = a_i + b_i(R_{M,t} - R_{f,t}) + s_i SMB_t + e_{i,t} \tag{3.1}$$

The three-factor model regression is

$$R_{i,t} - R_{f,t} = a_i + b_i(R_{M,t} - R_{f,t}) + s_i SMB_t + h_i HML_t + e_{i,t} \tag{3.2}$$

and the five-factor model regression is

$$R_{i,t} - R_{F,t} = a_i + b_i(R_{M,t} - R_{F,t}) + s_i SMB_t + h_i HML_t + r_i RMW_t + c_i CMA_t + e_{i,t} \tag{3.3}$$

Note that the details of the five-factor model were also discussed in Section 1.1.

The left-hand-side (LHS) variables are the excess returns of the 16 portfolios (see Section 2.2 of Chapter 2 for the detailed construction of these portfolios) and the right-hand-side (RHS) variables are the factors we constructed under the five methods.

The first three tables (Tables 3.19 to Table 3.21) pertain to the three models constructed from the first of the five sets of factors. We will discuss these three tables first in detail, then pick up differences in regressions across the five sets of factors that are constructed using the different methods. The summary of the regression analysis is that the RHS variables of the two-factor model explains reasonably well the LHS 16 portfolios' excess returns and the three- and five-factor models add a little more explanatory power to the two-factor model, but the amount is not large. As shown in Table 3.19, the adjusted R^2s are all above 90% except for the big stocks in the last row. These high adjusted R^2s leave very little room for other factors to improve. However, there are problems in all of the three models (also see details below). These problems are three fold: the problems in the intercepts, the irregularity in the slopes for size, and the inconsistency in the slopes of the B/M ratio. Interestingly, unlike in the US market, documented by Fama and French (2015), where the micro-cap firms invest a lot despite low profitability, the micro-cap firms in China do not behave in such a manner. Nevertheless, the regression coefficients of China imply problems of its own which may relate to this country's specific political characteristics and structures.

All models have high explanatory power, the five-factor model adds little explanatory power to the three-factor model

As shown in Tables 3.19 to Table 3.21, the adjusted R^2s were high for all three models (ranging from 0.79 to 0.97 for the two-factor model in Table 3.19 and 0.89 to 0.97 for the three-factor model in Table 3.20), and 0.90 to 0.98 for the five-factor model in Table 3.21. As summarized in Table 3.34, the adjusted R^2s did not change much from the the two factor to the three-factor model, and from the three-factor model to the five-factor model. The market and size factors combined can explain well the left-hand-side portfolios: their t-tests are mostly high in all sets of models. In all Tables 3.19 to 3.33, the lowest R^2 values are for the big stocks (more discussion on this later). Specifically, the market factor has a coefficient close to one for all of the 16 portfolios (the coefficients range from 0.92 to 1.09). This result partially supports the theory of the CAPM that the market factor explains stock return variations (the t-test for the market are mostly insignificant when tested against $\beta = 1$ except for some small and low B/M portfolios and some large and high B/M portfolios). That is, the market factor captures most of the stock return variations, even though there are a few stock return variations explained by some other potential factors. Although not shown here, we can report that the CAPM model for this dataset has market slopes of close to one and its average adjusted R^2s is 0.72.

The intercepts, however, are large in all models

Intercepts are critical in judging the performance of an asset pricing model. If the intercepts are, however, statistically significant and are non-zero, it implies there is a pattern in the portfolios' returns that are not captured by the factors. In this dataset, our first problem in all sets of the models was the statistically significant non-zero intercepts. In the two-factor model in Table 3.19, intercepts ranged from -1.28 to 0.16, their t-tests ranged from -5.33 to 0.50 and using t=2.58 as a threshold, 11 out of the 16 t-values are above 2.58 indicating these intercepts are significantly different from zero. In the three-factor model in Table 3.20, intercepts range from -0.84 to -0.16, and their t-tests ranged from -4.60 to -1.14. Using t=2.58 or p=0.01 as a threshold, 8 out of the 16 t-values are above 2.58, indicating these intercepts are significantly different from zero. In the five-factor model in Table 3.21 intercepts range from -0.70 to -0.15 and t-tests value ranged from -3.95 to -0.46. Using t=2.58 as a threshold, 9 out of the 16 t-values are above 2.58, indicating these intercepts are significantly different from zero. However, in the five-factor model, the intercepts are still high, at least compared with the study done in the US market in Fama and French (2015)[3]. These statistically significant intercepts may be harmful when the Fama-French multi-factor models are used as a tool to analyze equity fund performance. For example, in analysing equity mutual fund performance, the factors were regressed on mutual funds returns. The regression's intercepts are used to judge the performance of the mutual fund. This method works under the assumption that the factors used are good explanatory factors that explain the variation in stock returns. Therefore, since the models we examined in China produced significant intercepts, using the two-, three-, and five-factor models to analyze mutual fund performance in China may create inconsistent or wrong conclusions.

Problem in extremely large portfolios

Figure 3.1 shows the graphical representation of Table 3.20 – regression results from the three-factor model whose factors were constructed using construction method 1 specified in Table 3.5. Although the patterns described in the graph are exactly the same as that of numerical tables, the patterns became much clearer using a graph rather than numerical tables due to the fact that our eyes find it hard to picture a large set of numbers.

Hence, as very clearly revealed in Figure 3.1, the second problem lies in the slopes of the size factors in the extremely large-cap portfolios. In the three-factor model, the slopes dropped from small portfolios to big portfolios, but the drops

[3]The study reported that using the five-factor model, the regression generated a set of intercepts ranging from -0.29 to 0.18 – a much smaller range compared with our results here.

became extremely sudden when moving from size quartile three to size quartile four. For example, the slopes for the size factor in the BM1 quartile in the three-factor models shown in Table 3.20 are 1.17, 1.14, 0.93 and 0.06. The drop from 0.93 to 0.06 is dramatic compared with the previous drops. This is more clearly shown in Figure 3.1 or Figure 3.2. In each of the four B/M quartiles, slopes for size (s) decreases from small to big portfolios, but the drops are large at the last size quartile. This unusual behaviour implies that there may be some unseen characteristics embedded in the large stocks in China, at least in this data set.

Figure 3.1: The slope of Size factor (s) in the three-factor model in Table 3.20.

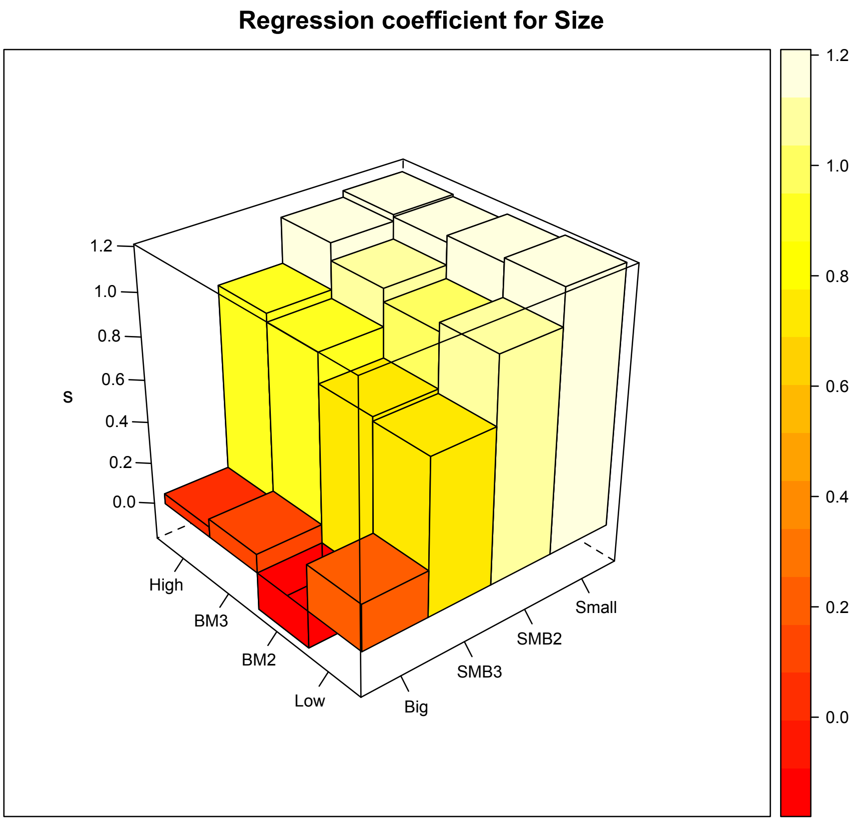
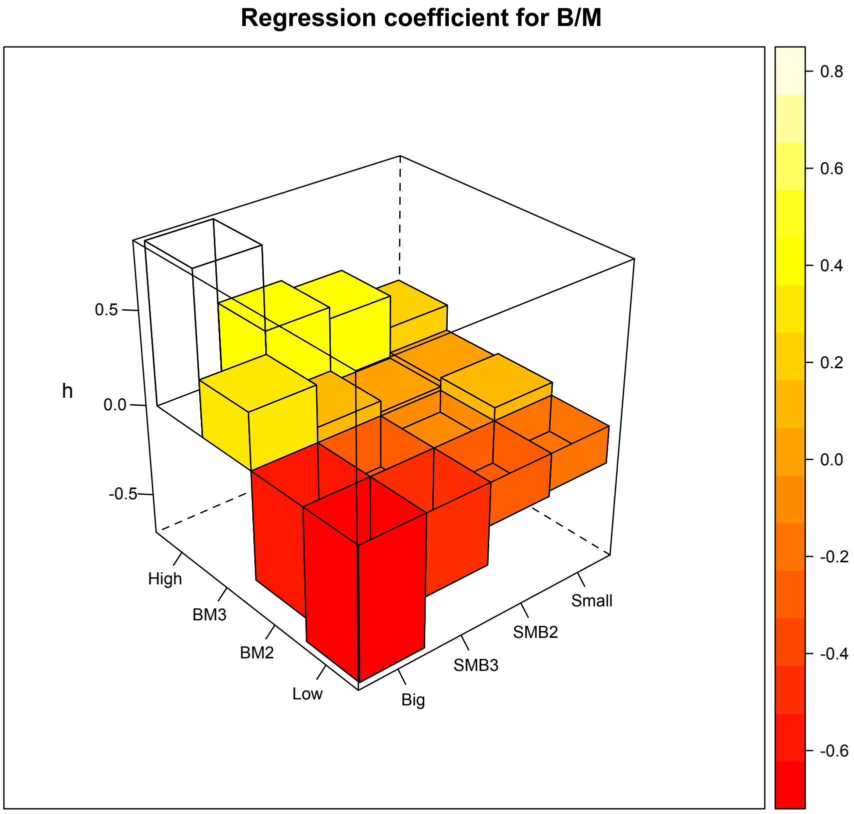


Figure 3.2: The slops of B/M (h) in the three-factor model (refer to equation in the Table 3.20).



The RMW and CMA factors do not add much additional explanatory power to the three-factor model

Unlike the patterns found in the US market Fama and French (2015), in China the RMW and CMA factors together do not add much explanatory power to the three-factor model judged by the regressions' adjusted R^2s. The adjusted R^2s for the 16 portfolios in the five-factor model were, in general, only slightly higher than those in the three-factor model. For example, the adjusted R^2 for the left-corner portfolio – the micro cap and extreme-value portfolio – in the three-factor model is 0.95 (Table 3.20), and it is 0.96 in the five-factor model (Table 3.21) – just slightly bigger. Most of the slopes for the RMW (Table 3.21) factor are also statistically insignificant (except for the slopes of portfolios S1L1, S2L1, and S2L3). This is shown in both the size of the slopes and t-test of those slopes. The slopes for RMW are mostly small, and there is no systematic change along the size columns or the B/M rows. The t-tests are also small in general. Even though there are some bigger t-tests in absolute value (e.g., -5.78 and -4.20), the corresponding slopes are in fact small which means when the factor change in value the corresponding changes in value of the portfolios are small.

As shown in Table 3.21, the slopes for the CMA factor have a similar story as those of the RMW factor. Most of the slopes for the CMA factor are also statistically insignificant. This is shown in both the size of the slopes and the t-test of those slopes. The slopes for CMA are mostly small and there is little systematic change along the size columns or the B/M rows. The t-tests are also mostly small (except for portfolios S3L1, S4L1, S2L2, S3L3, S3L3, S4L3, and S3L4). Even though there are some bigger t-tests (e.g., 6.22 and 4.68), the corresponding slopes are in fact small, which means when the factor changes in the value of the portfolios are small.

The five sets of factors produce similar regressions intercepts and adjusted R^2s

Table 3.19 to Table 3.33 show that models form different versions of factors given similar results for the regression intercepts and regression adjusted R^2s. For each of the five two-factor models, the average intercepts are -0.60, -0.41, -0.61, -0.61, and -0.56 (with the average t-tests of -2.79, -2.57, -2.80, -2.36 and -2.57, respectively); For each of the five- and three- factor models, the average intercepts are -0.54, -0.56, -0.59, -0.49 and -0.56 (with the average t-tests of -2.80, -2.67, -2.93, -2.24 and -2.69, respectively); For each of the five five - factor models, the average intercepts are -0.46, -0.41, -0.45, -0.38 and -0.48 (with the average t-tests of -2.35, -1.99, -2.23, -1.70, and -2.28 respectively). There is no obvious difference among the five sets of factors expressed by the intercepts. Similarly, the average adjusted R^2s of each of the five sets of two-factor models are 92.31%, 92.25%, 92.50%, 91.56% and 92.25% (Table 3.34). The average adjusted R^2s of each of the five sets of three – factor models are 94.46%, 93.54%, 94.27%, 93.35% and 94.00% (Table 3.34). The average adjusted R^2 of each of the five sets of five-factor models are 94.65%, 94.26%, 94.73%, 93.62%, and 94.27% (Table 3.34). Again, there is no obvious difference among the five sets of factors expressed through regressions' average adjusted R^2.

3.1.5 The Comparison of Models' Performance between the US and the Chinese Markets

As a final topic of this section, it would be interesting to compare the resulting models' performance in this study with that of Fama and French (2015). We will focus on the models' problem in the US and China respectively.

As specified in Fama and French (2015), the problem of the five-factor model in the US market was in some of the small portfolios with low profitability, and despite the low profitability, they invest aggressively. This phenomenon is hard to explain using a theory of behavioral finance.

The problem with the five-factor model in China is in two fold: First, the investment style and the profitability are not even significant factors in this Chinese stock market. Second, as shown in Table 3.10 to 3.14, the SMB and HML factors were highly correlated, which created multicollinearity problem. Removing the HML factor in the model for the Chinese market removed this problem; however, a two-factor model containing a market factor and an SMB factor produced significant intercepts which can easily reject the eligibility of the two-factor model.

3.1.6 Regression Tables

Table 3.19: Regressions of the 16 value-weighted Size-B/M sorted portfolios; January 2000 to March 2015. At the end of each month, four size (from small to big) intervals and four B/M (from low to high) intervals are determined independently. Stocks that fit each of the total 16 resulting intervals are formed as portfolios. We take their monthly excess returns as the LHS variable in the regression. The RHS variables of the regressions are the two factors from factor set 1 (shown in Table 3.5) including a market factor, and a size factor.

$$R_{i,t} - R_{F,t} = a_i + b_i(R_{M,t} - R_{F,t}) + s_i SMB_t + e_{i,t}$$

Factor set 1 Two-factor model

	Low	B/M 2	B/M 3	High	Low	B/M 2	B/M 3	High
	a (Intercept)				**t(a)**			
Small	-0.70	-0.38	-0.19	-0.18	-3.03	-2.13	-1.29	-1.03
Size 2	-1.07	-0.66	-0.55	-0.46	-5.33	-4.04	-3.19	-2.90
Size 3	-1.16	-0.81	-0.66	-0.54	-4.27	-3.31	-3.50	-2.76
Big	-1.28	-0.75	-0.35	0.16	-4.18	-2.81	-1.41	0.50
	b (Market)				**t(b)** ($h_0 = 1$)			
Small	0.91	0.95	0.96	0.96	-3.30	-2.40	-2.23	-1.97
Size 2	0.98	0.98	1.00	1.01	-0.84	-1.03	0.00	0.53
Size 3	1.00	1.01	1.07	1.06	0.00	0.35	3.12	2.62
Big	1.01	1.01	1.02	0.92	0.00	0.32	0.67	-2.16
	s (Size)				**t(s)**			
Small	1.24	1.16	1.14	1.12	31.44	38.39	43.69	38.06
Size 2	1.08	1.02	1.04	1.05	31.36	36.14	34.94	38.26
Size 3	0.83	0.82	0.87	0.84	17.76	19.56	26.62	25.10
Big	0.38	-0.06	0.01	-0.15	7.12	-1.38	0.12	-2.75

Adjusted R-Squared

	Low	B/M 2	B/M 3	High
Small	0.94	0.96	0.97	0.96
Size 2	0.95	0.96	0.96	0.97
Size 3	0.90	0.92	0.95	0.95
Big	0.85	0.86	0.88	0.79

Table 3.20: Regressions of the 16 value-weighted Size-B/M sorted portfolios; January 2000 to March 2015. At the end of each month, four size (from small to big) intervals and four B/M (from low to high) intervals are determined independently. Stocks that fit each of the total 16 resulting intervals are formed as portfolios. We take their monthly excess returns as the LHS variable in the regression. The RHS variables of the regressions are the three factors from factor set 1 (shown in Table 3.5) including a market factor, a size factor and a HML factor.

$$R_{i,t} - R_{F,t} = a_i + b_i(R_{M,t} - R_{F,t}) + s_i SMB_t + h_i HML_t + e_{i,t}$$

Factor set 1 Three-factor model

	Low	B/M 2	B/M 3	High	Low	B/M 2	B/M 3	High
	a (Intercept)				**t(a)**			
Small	-0.48	-0.36	-0.16	-0.25	-2.36	-2.02	-1.14	-1.53
Size 2	-0.84	-0.53	-0.52	-0.65	-4.60	-3.55	-2.99	-4.19
Size 3	-0.80	-0.55	-0.66	-0.77	-3.37	-2.38	-3.35	-4.07
Big	-0.74	-0.36	-0.58	-0.44	-3.29	-1.59	-2.41	-1.99
	b (Market)				**t(b)** ($h_0 = 1$)			
Small	0.92	0.97	0.97	0.98	-3.36	-1.45	-1.79	-1.05
Size 2	0.99	0.99	1.01	1.04	-0.47	-0.58	0.51	2.22
Size 3	1.02	1.02	1.09	1.09	0.72	0.74	3.93	4.13
Big	1.00	1.00	1.02	0.95	0.00	0.00	0.72	-1.95
	s (Size)				**t(s)**			
Small	1.20	1.19	1.16	1.17	31.22	35.28	42.36	37.93
Size 2	1.03	1.00	1.06	1.14	29.92	35.68	32.98	39.06
Size 3	0.72	0.74	0.89	0.93	16.19	17.21	23.91	26.32
Big	0.20	-0.19	0.10	0.06	4.65	-4.55	2.15	1.53
	h (B/M)				**t(h)**			
Small	-0.22	0.07	0.04	0.18	-3.76	1.30	0.92	3.93
Size 2	-0.24	-0.12	0.01	0.34	-4.77	-2.79	0.25	7.90
Size 3	-0.45	-0.30	0.06	0.40	-6.79	-4.61	1.14	7.46
Big	-0.74	-0.58	0.31	0.82	-11.76	-9.13	4.56	13.21

Adjusted R-Squared

	Low	B/M 2	B/M 3	High
Small	0.95	0.96	0.97	0.97
Size 2	0.96	0.97	0.97	0.97
Size 3	0.93	0.93	0.95	0.96
Big	0.92	0.91	0.89	0.90

Table 3.21: Regressions of the 16 value-weighted Size-B/M sorted portfolios; January 2000 to March 2015. At the end of each month, four size (from small to big) intervals and four B/M (from low to high) intervals are determined independently. Stocks that fit each of the total 16 resulting intervals are formed as portfolios. We take their monthly excess returns as the LHS variable in the regression. The RHS variables of the regressions are the five factors from factor set 1 (shown in Table 3.5) including a market factor, a size factor, a HML factor, a profitability factor (RMW) and an investment style factor (CMA).

$$R_{i,t} - R_{F,t} = a_i + b_i(R_{M,t} - R_{F,t}) + s_i SMB_t + h_i HML_t + r_i RMW_t + c_i CMA_t + e_{i,t}$$

Factor set 1 Five-factor model

	Low	B/M 2	B/M 3	High	Low	B/M 2	B/M 3	High
	a (Intercept)				**t(a)**			
Small	-0.15	-0.30	-0.07	-0.20	-0.74	-1.58	-0.46	-1.17
Size 2	-0.59	-0.48	-0.58	-0.64	-3.24	-3.19	-3.47	-3.95
Size 3	-0.70	-0.62	-0.64	-0.59	-3.01	-2.63	-3.24	-3.05
Big	-0.62	-0.53	-0.34	-0.31	-2.68	-2.30	-1.49	-1.34
	b (Market)				**t(b)** ($h_0 = 1$)			
Small	0.89	0.97	0.97	0.97	-4.95	-1.41	-1.75	-1.54
Size 2	0.96	0.98	1.02	1.03	-1.97	-1.17	1.04	1.65
Size 3	0.99	1.01	1.08	1.08	-0.38	0.38	3.59	3.67
Big	0.98	1.00	1.00	0.94	-0.76	0.00	0.00	-2.30
	s (Size)				**t(s)**			
Small	0.92	1.13	1.08	1.13	19.32	23.63	27.77	24.94
Size 2	0.81	0.96	1.11	1.13	19.35	24.28	25.07	27.80
Size 3	0.63	0.79	0.86	0.78	11.65	13.65	17.46	17.67
Big	0.09	-0.05	-0.11	-0.05	3.88	-2.22	0.26	0.39
	h (B/M)				**t(h)**			
Small	-0.22	0.07	0.04	0.18	-4.16	1.29	0.91	3.92
Size 2	-0.25	-0.12	0.01	0.34	-5.11	-2.91	0.24	7.95
Size 3	-0.45	-0.30	0.06	0.39	-7.25	-4.75	1.16	7.64
Big	-0.74	-0.57	0.30	0.82	-11.98	-9.26	4.98	13.29
	r (Profitability)				**t(r)**			
Small	-0.49	-0.08	-0.11	-0.03	-5.78	-1.02	-1.63	-0.35
Size 2	-0.33	0.02	0.22	0.04	-4.20	0.35	3.07	0.58
Size 3	0.06	0.22	0.11	-0.20	0.55	2.12	1.30	-2.36
Big	-0.08	0.19	-0.13	-0.14	-0.75	1.84	-1.27	-1.38
	c (Investment style)				**t(c)**			
Small	0.10	0.04	0.10	0.12	1.23	0.55	1.65	1.72
Size 2	0.17	0.21	0.23	0.14	2.32	3.36	3.41	2.09
Size 3	0.44	0.23	0.33	0.21	4.68	2.43	4.07	2.63
Big	0.25	-0.20	0.58	0.17	2.63	-2.17	6.22	1.77

Adjusted R-Squared

	Low	B/M 2	B/M 3	High
Small	0.96	0.96	0.98	0.97
Size 2	0.96	0.97	0.97	0.97
Size 3	0.93	0.93	0.95	0.96
Big	0.92	0.91	0.90	0.90

Table 3.22: Regressions of the 16 value-weighted Size-B/M sorted portfolios; January 2000 to March 2015. At the end of each month, four size (from small to big) intervals and four B/M (from low to high) intervals are determined independently. Stocks that fit each of the total 16 resulting intervals are formed as portfolios. We take their monthly excess returns as the LHS variable in the regression. The RHS variables of the regressions are the two factors from factor set 2 (shown in Table 3.5) including a market factor and a SMB factor.

$$R_{i,t} - R_{F,t} = a_i + b_i(R_{M,t} - R_{F,t}) + s_i SMB_t + e_{i,t}$$

Factor set 2 Two-factor model

	Low	B/M 2	B/M 3	High	Low	B/M 2	B/M 3	High
	a (Intercept)				**t(a)**			
Small	-0.67	-0.33	-0.16	-0.14	-2.96	-1.74	-1.01	-0.75
Size 2	-1.04	-0.63	-0.52	-0.41	-5.17	-3.79	-2.86	-2.15
Size 3	-1.14	-0.78	-0.63	-0.49	-4.16	-3.19	-3.08	-2.22
Big	1.29	-0.79	-0.35	0.19	-4.31	-2.92	-1.39	0.62
	b (Market)				**t(b)** ($h_0 = 1$)			
Small	0.93	0.98	0.98	0.98	-2.64	-0.88	-1.07	-0.92
Size 2	1.00	1.00	1.02	1.03	0.00	0.00	0.93	1.32
Size 3	1.02	1.02	1.09	1.08	0.62	0.69	3.73	3.09
Big	1.01	1.01	1.02	0.92	0.28	0.31	0.68	-2.22
	s (Size)				**t(s)**			
Small	1.31	1.21	1.19	1.16	32.24	34.87	41.43	34.79
Size 2	1.14	1.07	1.09	1.08	31.21	35.42	33.09	30.79
Size 3	0.87	0.86	0.90	0.85	17.63	19.38	24.27	21.28
Big	0.42	-0.02	-0.002	-0.21	7.81	-0.44	-0.05	-3.76

Adjusted R-Squared

	Low	B/M 2	B/M 3	High
Small	0.94	0.96	0.97	0.96
Size 2	0.95	0.96	0.96	0.95
Size 3	0.90	0.92	0.95	0.94
Big	0.86	0.86	0.88	0.80

Table 3.23: Regressions of the 16 value-weighted Size-B/M sorted portfolios; January 2000 to March 2015. At the end of each month, four size (from small to big) intervals and four B/M (from low to high) intervals are determined independently. Stocks that fit each of the total 16 resulting intervals are formed as portfolios. We take their monthly excess returns as the LHS variable in the regression. The RHS variables of the regressions are the three factors from factor set 2 (shown in Table 3.5) including a market factor, a size factor and a HML factor.

$$R_{i,t} - R_{F,t} = a_i + b_i(R_{M,t} - R_{F,t}) + s_i SMB_t + h_i HML_t + e_{i,t}$$

Factor set 2 Three-factor model

	Low	B/M 2	B/M 3	High	Low	B/M 2	B/M 3	High
	a (Intercept)				**t(a)**			
Small	-0.50	-0.38	-0.18	-0.27	-2.24	-1.92	-1.13	-1.46
Size 2	-0.85	-0.54	-0.59	-0.73	-4.38	-3.21	-2.80	-3.81
Size 3	-0.79	-0.55	-0.72	-0.83	-3.18	-2.34	-3.21	-3.94
Big	-0.73	-0.34	-0.56	-0.40	-3.23	-1.58	-2.36	-1.85
	b (Market)				**t(b)** ($h_0 = 1$)			
Small	0.92	0.98	0.97	0.98	-3.12	-0.88	-1.61	-0.95
Size 2	0.99	0.99	1.02	1.04	-0.44	-0.52	0.92	1.98
Size 3	1.00	1.01	1.09	1.10	0.00	0.37	3.73	4.35
Big	0.99	0.99	1.03	0.95	-0.38	-0.38	1.07	-1.95
	s (Size)				**t(s)**			
Small	1.24	1.23	1.20	1.22	28.43	31.80	37.49	33.71
Size 2	1.06	1.03	1.09	1.18	27.69	31.24	29.67	34.28
Size 3	0.73	0.77	0.91	0.97	14.89	16.43	22.21	24.80
Big	0.19	-0.20	0.09	0.04	4.34	-4.46	1.89	0.86
	h (B/M)				**t(h)**			
Small	-0.23	0.06	0.03	0.17	-3.63	1.03	0.67	3.37
Size 2	-0.25	-0.13	0.00	0.34	-4.60	-2.69	0.05	6.84
Size 3	-0.47	-0.30	0.05	0.39	-6.67	-4.59	0.93	7.00
Big	-0.75	-0.58	0.30	0.80	-11.78	-9.08	4.43	12.85

R Square

	Low	B/M 2	B/M 3	High
Small	0.94	0.96	0.97	0.96
Size 2	0.96	0.97	0.96	0.96
Size 3	0.92	0.93	0.95	0.95
Big	0.92	0.91	0.89	0.90

Table 3.24: Regressions of the 16 value-weighted Size-B/M sorted portfolios; January 2000 to March 2015. At the end of each month, four size (from small to big) intervals and four B/M (from low to high) intervals are determined independently. Stocks that fit each of the total 16 resulting intervals are formed as portfolios. We take their monthly excess returns as the LHS variable in the regression. The RHS variables of the regressions are the five factors from factor set 2 (shown in Table 3.5) including a market factor, a size factor, a HML factor, a return on asset factor (RMW) and an investment style factor (CMA).

$$R_{i,t} - R_{F,t} = a_i + b_i(R_{M,t} - R_{F,t}) + s_iSMB_t + h_iHML_t + r_iRMW_t + c_iCMA_t + e_{i,t}$$

Factor set 2 Five-factor model

	Low	B/M 2	B/M 3	High	Low	B/M 2	B/M 3	High
	a (Intercept)				**t(a)**			
Small	-0.09	-0.23	-0.01	-0.13	-0.43	-1.12	-0.06	-0.71
Size 2	-0.54	-0.42	-0.51	-0.57	-2.93	-2.53	-2.80	-3.20
Size 3	-0.63	-0.56	-0.58	-0.55	-2.63	-2.35	-2.86	-2.80
Big	-0.60	-0.53	-0.34	-0.23	-2.58	-2.29	-1.49	-1.02
	b (Market)				**t(b)** ($h_0 = 1$)			
Small	0.89	0.96	0.96	0.97	-4.73	-1.76	-2.18	-1.42
Size 2	0.96	0.98	1.01	1.03	-1.91	-1.07	0.48	1.49
Size 3	0.98	1.01	1.08	1.07	-0.74	0.37	3.45	3.17
Big	0.97	1.00	1.00	0.94	-1.15	0.00	0.00	-2.31
	s (Size)				**t(s)**			
Small	0.90	1.10	1.05	1.10	14.27	17.76	21.06	19.21
Size 2	0.80	0.92	1.08	1.09	14.00	18.18	19.12	20.06
Size 3	0.59	0.77	0.83	0.77	7.96	10.42	13.27	12.78
Big	0.08	-0.05	-0.12	-0.12	1.07	-0.72	-1.66	-1.65
	h (B/M)				**t(h)**			
Small	-0.22	0.06	0.03	0.17	-4.09	1.06	0.72	3.48
Size 2	-0.25	-0.13	0.00	0.34	-5.03	-2.83	0.07	7.07
Size 3	-0.46	-0.30	0.06	0.39	-7.17	-4.72	1.01	7.44
Big	-0.75	-0.58	0.30	0.80	-12.02	-9.28	4.96	13.12
	r (Profitability)				**t(r)**			
Small	-0.57	-0.18	-0.19	-0.12	-6.55	-2.07	-2.73	-1.49
Size 2	-0.39	-0.06	0.13	-0.05	-4.94	-0.86	1.70	-0.71
Size 3	-0.02	0.15	0.04	-0.25	-0.23	1.46	0.46	-3.03
Big	-0.10	0.18	-0.12	-0.20	-1.02	1.87	-1.29	-2.09
	c (Investment style)				**t(c)**			
Small	0.18	0.15	0.20	0.22	2.24	1.82	3.03	3.01
Size 2	0.24	0.30	0.34	0.24	3.27	4.50	4.59	3.41
Size 3	0.51	0.31	0.41	0.27	5.34	3.19	4.96	3.49
Big	0.26	-0.21	0.57	0.19	2.84	-2.23	6.27	2.07

R Square

	Low	B/M 2	B/M 3	High
Small	0.96	0.96	0.97	0.96
Size 2	0.96	0.97	0.96	0.97
Size 3	0.93	0.93	0.95	0.96
Big	0.92	0.91	0.91	0.90

Table 3.25: Regressions of the 16 value-weighted Size-B/M sorted portfolios; January 2000 to March 2015. At the end of each month, four size (from small to big) intervals and four B/M (from low to high) intervals are determined independently. Stocks that fit each of the total 16 resulting intervals are formed as portfolios. We take their monthly excess returns as the LHS variable in the regression. The RHS variables of the regressions are the two factors from factor set 3 (shown in Table 3.5) including a market factor and a SMB factor.

$$R_{i,t} - R_{F,t} = a_i + b_i(R_{M,t} - R_{F,t}) + s_i SMB_t + e_{i,t}$$

Factor set 3 Two-factor model

	Low	B/M 2	B/M 3	High	Low	B/M 2	B/M 3	High
	a (Intercept)				**t(a)**			
Small	-0.72	-0.39	-0.21	-0.19	-3.33	-2.09	-1.38	-1.05
Size 2	-1.09	-0.68	-0.57	-0.46	-5.49	-4.30	-3.22	-2.47
Size 3	-1.18	-0.81	-0.66	-0.52	-4.42	-3.33	-3.30	-2.39
Big	-1.31	-0.78	-0.35	0.18	-4.37	-2.90	-1.39	0.60
	b (Market)				**t(b)** ($h_0 = 1$)			
Small	1.06	1.12	1.12	1.11	3.18	5.58	6.80	5.34
Size 2	1.13	1.12	1.15	1.16	5.64	6.54	7.30	7.35
Size 3	1.12	1.12	1.19	1.18	3.86	4.21	8.12	7.06
Big	1.06	1.01	1.02	0.90	1.73	0.32	0.68	-2.77
	s (Size)				**t(s)**			
Small	0.95	0.88	0.87	0.85	33.69	36.60	43.81	36.49
Size 2	0.83	0.78	0.80	0.78	31.92	37.71	34.53	32.18
Size 3	0.64	0.62	0.65	0.62	18.31	19.43	24.75	21.46
Big	0.31	-0.02	0.00	-0.14	7.87	-0.56	0.00	-3.45

Adjusted R-Squared

	Low	B/M 2	B/M 3	High
Small	0.95	0.96	0.97	0.96
Size 2	0.95	0.97	0.96	0.96
Size 3	0.91	0.92	0.95	0.94
Big	0.86	0.86	0.88	0.80

Table 3.26: Regressions of the 16 value-weighted Size-B/M sorted portfolios; January 2000 to March 2015. At the end of each month, four size (from small to big) intervals and four B/M (from low to high) intervals are determined independently. Stocks that fit each of the total 16 resulting intervals are formed as portfolios. We take their monthly excess returns as the LHS variable in the regression. The RHS variables of the regressions are the five factors from factor set 3 (shown in Table 3.5) including a market factor, a size factor, and a HML factor.

$$R_{i,t} - R_{F,t} = a_i + b_i(R_{M,t} - R_{F,t}) + s_i SMB_t + h_i HML_t + e_{i,t}$$

Factor set 3 Three-factor model

	Low	B/M 2	B/M 3	High	Low	B/M 2	B/M 3	High
	a (Intercept)				**t(a)**			
Small	-0.63	-0.44	-0.23	-0.29	-2.88	-2.35	-1.51	-1.66
Size 2	-0.98	-0.59	-0.54	-0.66	-4.94	-3.75	-3.03	-3.88
Size 3	-0.87	-0.58	-0.68	-0.78	-3.58	-2.50	-3.33	-3.93
Big	-0.77	-0.37	-0.57	-0.40	-3.57	-1.67	-2.41	-1.90
	b (Market)				**t(b)** ($h_0 = 1$)			
Small	1.07	1.12	1.12	1.13	2.74	5.49	6.64	6.28
Size 2	1.12	1.11	1.14	1.18	5.17	5.97	6.67	8.98
Size 3	1.08	1.09	1.20	1.22	2.82	3.31	8.26	9.41
Big	0.99	0.95	1.05	0.98	-0.39	-1.95	1.78	-0.81
	s (Size)				**t(s)**			
Small	0.92	0.90	0.87	0.88	29.67	33.67	39.67	35.04
Size 2	0.79	0.79	0.79	0.85	28.05	33.37	30.70	34.74
Size 3	0.54	0.55	0.66	0.70	15.57	16.51	22.40	24.61
Big	0.13	-0.15	0.07	0.05	4.33	4.93	2.15	1.65
	h (B/M)				**t(h)**			
Small	-0.11	0.06	0.03	0.13	-2.20	1.49	0.79	3.14
Size 2	-0.13	-0.10	-0.03	0.24	-2.94	-2.90	-0.62	6.19
Size 3	-0.36	-0.27	0.02	0.30	-6.66	-5.22	0.48	6.68
Big	-0.62	-0.49	0.26	0.65	-12.77	-9.80	4.90	14.32

R Square

	Low	B/M 2	B/M 3	High
Small	0.95	0.96	0.97	0.96
Size 2	0.95	0.97	0.96	0.97
Size 3	0.92	0.93	0.95	0.95
Big	0.93	0.91	0.89	0.91

Table 3.27: Regressions of the 16 value-weighted Size-B/M sorted portfolios; January 2000 to March 2015. At the end of each month, four size (from small to big) intervals and four B/M (from low to high) intervals are determined independently. Stocks that fit each of the total 16 resulting intervals are formed as portfolios. We take their monthly excess returns as the LHS variable in the regression. The RHS variables of the regressions are the five factors from factor set 3 (shown in Table 3.5) including a market factor, a size factor, a HML factor, a return on asset factor (RMW) and an investment style factor (CMA).

$$R_{i,t} - R_{F,t} = a_i + b_i(R_{M,t} - R_{F,t}) + s_i SMB_t + h_i HML_t + r_i RMW_t + c_i CMA_t + e_{i,t}$$

Factor set 3 Five-factor model

	Low	B/M 2	B/M 3	High	Low	B/M 2	B/M 3	High
	a (Intercept)				**t(a)**			
Small	-0.31	-0.31	-0.09	-0.21	-1.44	-1.63	-0.55	-1.13
Size 2	-0.71	-0.45	-0.50	-0.60	-3.63	-2.88	-2.80	-3.37
Size 3	-0.65	-0.47	-0.56	-0.54	-2.81	-2.02	-2.75	-2.73
Big	-0.54	-0.49	-0.37	-0.39	-2.46	-2.15	-1.60	-1.78
	b(Market)				**t(b)** ($h_0 = 1$)			
Small	0.99	1.09	1.08	1.11	-0.35	3.50	3.85	4.50
Size 2	1.05	1.08	1.13	1.17	1.92	3.81	5.51	7.16
Size 3	1.03	1.06	1.17	1.16	0.98	1.94	6.25	6.02
Big	0.94	0.98	1.00	0.98	-2.05	-0.66	0.00	-0.68
	s (Size)				**t(s)**			
Small	0.63	0.79	0.74	0.80	9.65	13.27	15.45	14.35
Size 2	0.55	0.63	0.75	0.79	9.17	13.03	13.75	14.53
Size 3	0.34	0.45	0.55	0.48	4.84	6.30	8.78	7.91
Big	-0.08	-0.04	-0.11	0.04	-1.20	-0.62	-1.52	0.65
	h (B/M)				**t(h)**			
Small	-0.13	0.05	0.01	0.12	-2.89	1.23	0.42	2.93
Size 2	-0.15	-0.12	-0.03	0.23	-3.60	-3.42	-0.85	6.03
Size 3	-0.39	-0.29	0.01	0.28	-7.78	-5.67	0.18	6.45
Big	-0.65	-0.47	0.24	0.68	-13.60	-9.62	4.81	14.19
	r (Profitability				**t(r)**			
Small	-0.48	-0.14	-0.17	-0.08	-5.03	-1.64	-2.43	-0.98
Size 2	-0.35	-0.12	0.05	-0.04	-4.06	-1.70	0.69	-0.55
Size 3	-0.13	-0.03	-0.05	-0.30	-1.30	-0.27	-0.55	-3.42
Big	-0.29	0.12	-0.13	0.04	-2.97	1.16	-1.30	0.39
	c (Investment style)				**t(c)**			
Small	0.12	0.15	0.17	0.15	1.50	2.04	2.77	2.14
Size 2	0.19	0.25	0.30	0.16	2.54	4.15	4.49	2.34
Size 3	0.54	0.36	0.36	0.20	6.14	4.04	4.70	2.66
Big	0.24	-0.20	0.46	0.12	2.82	-2.30	5.20	1.41

R Square

	Low	B/M 2	B/M 3	High
Small	0.95	0.96	0.97	0.96
Size 2	0.96	0.97	0.97	0.97
Size 3	0.94	0.93	0.95	0.96
Big	0.93	0.91	0.91	0.91

Table 3.28: Regressions of the 16 value-weighted Size-B/M sorted portfolios; January 2000 to March 2015. At the end of each month, four size (from small to big) intervals and four B/M (from low to high) intervals are determined independently. Stocks that fit each of the total 16 resulting intervals are formed as portfolios. We take their monthly excess returns as the LHS variable in the regression. The RHS variables of the regressions are the two factors from factor set 4 (shown in Table 3.5) including a market factor and a size factor.

$$R_{i,t} - R_{F,t} = a_i + b_i(R_{M,t} - R_{F,t}) + s_i SMB_t + e_{i,t}$$

Factor set 4 Two-factor model

	Low	B/M 2	B/M 3	High	Low	B/M 2	B/M 3	High
	a (Intercept)				**t(a)**			
Small	-0.65	-0.32	-0.14	-0.13	-2.63	-1.55	-0.76	-0.64
Size 2	-1.03	-0.62	-0.50	-0.42	-4.70	-3.30	-2.37	-2.17
Size 3	-1.11	-0.77	-0.62	-0.50	-3.79	-2.94	-2.87	-2.33
Big	-1.25	-0.80	-0.35	0.19	-4.03	-2.96	-1.39	0.61
	b (Market)				**t(b)** ($h_0 = 1$)			
Small	0.86	0.91	0.92	0.92	-4.75	-3.60	-3.53	-3.33
Size 2	0.94	0.94	0.97	0.97	-2.29	-2.69	-1.18	-1.31
Size 3	0.98	0.98	1.04	1.04	-0.57	-0.64	1.55	1.56
Big	1.00	1.01	1.02	0.94	0.00	0.31	0.67	-1.62
	s (Size)				**t(s)**			
Small	1.25	1.16	1.13	1.12	28.82	31.53	34.08	31.71
Size 2	1.09	1.02	1.03	1.05	28.26	30.93	27.77	31.14
Size 3	0.81	0.81	0.86	0.83	15.71	17.72	22.58	22.20
Big	0.36	-0.01	0.00	-0.20	6.60	-0.14	-0.06	-3.75

Adjusted R-Squared

	Low	B/M 2	B/M 3	High
Small	0.93	0.95	0.96	0.95
Size 2	0.94	0.95	0.95	0.96
Size 3	0.89	0.91	0.94	0.94
Big	0.84	0.86	0.88	0.80

Table 3.29: Regressions of the 16 value-weighted Size-B/M sorted portfolios; January 2000 to March 2015. At the end of each month, four size (from small to big) intervals and four B/M (from low to high) intervals are determined independently. Stocks that fit each of the total 16 resulting intervals are formed as portfolios. We take their monthly excess returns as the LHS variable in the regression. The RHS variables of the regressions are the three factors from factor set 4 (shown in Table 3.5) including a market factor, a size factor and a HML factor.

$$R_{i,t} - R_{F,t} = a_i + b_i(R_{M,t} - R_{F,t}) + s_i SMB_t + h_i HML_t + e_{i,t}$$

Factor set 4 Three-factor model

	Low	B/M 2	B/M 3	High	Low	B/M 2	B/M 3	High
	a (Intercept)				**t(a)**			
Small	-0.40	-0.29	-0.09	-0.18	-1.70	-1.35	-0.45	-0.89
Size 2	-0.78	-0.45	-0.43	-0.61	-3.77	-2.46	-1.98	-3.35
Size 3	-0.70	-0.48	-0.61	-0.75	-2.68	-1.96	-2.75	-3.80
Big	-0.66	-0.37	-0.56	-0.45	-2.79	-1.61	-2.30	-2.05
	b(Market)				**t(b)** ($h_0 = 1$)			
Small	0.86	0.91	0.92	0.92	-5.06	-3.60	-3.54	-3.34
Size 2	0.94	0.94	0.96	0.97	-2.50	-2.83	-1.60	-1.40
Size 3	0.98	0.98	1.04	1.04	-0.65	-0.69	1.55	1.72
Big	1.00	1.01	1.02	0.94	0.00	0.37	0.70	-2.36
	s (Size)				**t(s)**			
Small	1.18	1.15	1.12	1.14	26.80	29.03	31.33	30.00
Size 2	1.01	0.97	1.01	1.11	26.60	28.70	25.38	32.80
Size 3	0.68	0.72	0.85	0.91	14.09	15.85	20.88	24.94
Big	0.18	-0.14	0.07	-0.00	4.01	-3.28	1.45	-0.09
	h (B/M)				**t(h)**			
Small	-0.32	-0.05	-0.07	0.07	-4.82	-0.76	-1.36	1.20
Size 2	-0.33	-0.22	-0.09	0.25	-5.74	-4.33	-1.58	4.97
Size 3	-0.53	-0.36	-0.01	0.33	-7.20	-5.26	-0.20	6.00
Big	-0.76	-0.55	0.28	0.82	-11.56	-8.56	4.10	13.55

R Square

	Low	B/M 2	B/M 3	High
Small	0.94	0.95	0.96	0.95
Size 2	0.95	0.96	0.95	0.96
Size 3	0.91	0.92	0.94	0.95
Big	0.91	0.90	0.89	0.90

Table 3.30: Regressions of the 16 value-weighted Size-B/M sorted portfolios; January 2000 to March 2015. At the end of each month, four size (from small to big) intervals and four B/M (from low to high) intervals are determined independently. Stocks that fit each of the total 16 resulting intervals are formed as portfolios. We take their monthly excess returns as the LHS variable in the regression. The RHS variables of the regressions are the five factors from factor set 4 (shown in Table 3.5) including a market factor, a size factor, a HML factor, a return on asset factor (RMW) and an investment style factor (CMA).

$$R_{i,t} - R_{F,t} = a_i + b_i(R_{M,t} - R_{F,t}) + s_iSMB_t + h_iHML_t + r_iRMW_t + c_iCMA_t + e_{i,t}$$

Factor set 4 Five-factor model

	Low	B/M 2	B/M 3	High	Low	B/M 2	B/M 3	High
	a (Intercept)				**t(a)**			
Small	-0.00	-0.13	0.10	-0.02	-0.01	-0.61	0.49	-0.10
Size 2	-0.56	-0.34	-0.43	-0.56	-2.73	-1.81	-1.92	-2.94
Size 3	-0.53	-0.51	-0.57	-0.67	-1.99	-1.99	-2.44	-3.24
Big	-0.67	-0.56	-0.35	-0.29	-2.72	-2.39	-1.41	-1.31
	b(Market)				**t(b)** ($h_0 = 1$)			
Small	0.87	0.92	0.92	0.92	-5.32	-3.22	-3.68	-3.41
Size 2	0.95	0.95	0.96	0.97	-2.14	-2.35	-1.58	-1.40
Size 3	0.99	0.98	1.04	1.04	-0.33	-0.69	1.54	1.72
Big	1.00	1.00	1.03	0.94	0.00	0.00	1.08	-2.39
	s (Size)				**t(s)**			
Small	0.90	1.05	0.98	1.02	16.12	18.64	19.86	19.11
Size 2	0.88	0.89	1.01	1.08	16.63	18.59	17.61	22.02
Size 3	0.61	0.76	0.84	0.85	8.96	11.57	14.15	16.16
Big	0.16	-0.04	-0.03	-0.10	2.48	-0.70	-0.56	-1.71
	h (B/M)				**t(h)**			
Small	-0.32	-0.05	-0.07	0.07	-5.45	-0.85	-1.31	1.24
Size 2	-0.34	-0.22	-0.10	0.25	-6.06	-4.35	-1.55	4.84
Size 3	-0.56	-0.38	-0.02	0.33	-7.73	-5.34	-0.34	5.93
Big	-0.74	-0.52	0.24	0.81	-11.07	-8.20	3.60	13.28
	r (Profitability)				**t(r)**			
Small	-0.57	-0.21	-0.28	-0.25	-6.76	-2.42	-3.80	-3.04
Size 2	-0.26	-0.15	0.01	-0.07	-3.23	-1.99	0.12	-0.93
Size 3	-0.10	0.09	-0.03	-0.13	-0.97	0.95	-0.29	-1.68
Big	-0.07	0.17	-0.16	-0.18	-0.68	1.88	-1.68	-2.03
	c (Investment style)				**t(c)**			
Small	0.09	0.06	-0.01	0.01	1.00	0.64	-0.10	0.07
Size 2	0.12	0.04	0.01	0.02	1.43	0.49	0.06	0.21
Size 3	0.30	0.10	0.08	0.00	2.76	0.92	0.81	0.01
Big	-0.15	-0.22	0.31	0.11	-1.47	-2.27	3.13	1.19

R Square

	Low	B/M 2	B/M 3	High
Small	0.95	0.95	0.96	0.95
Size 2	0.95	0.96	0.94	0.96
Size 3	0.92	0.92	0.94	0.95
Big	0.91	0.91	0.90	0.91

Table 3.31: Regressions of the 16 value-weighted Size-B/M sorted portfolios; January 2000 to March 2015. At the end of each month, four size (from small to big) intervals and four B/M (from low to high) intervals are determined independently. Stocks that fit each of the total 16 resulting intervals are formed as portfolios. We take their monthly excess returns as the LHS variable in the regression. The RHS variables of the regressions are the two factors from factor set 5 (shown in Table 3.5) including a market factor and a size factor.

$$R_{i,t} - R_{F,t} = a_i + b_i(R_{M,t} - R_{F,t}) + s_i SMB_t + e_{i,t}$$

Factor set 5 Two-factor model

	Low	B/M 2	B/M 3	High	Low	B/M 2	B/M 3	High
	a (Intercept)				**t(a)**			
Small	-0.67	-0.33	-0.16	-0.14	-2.96	-1.74	-1.01	-0.75
Size 2	-1.04	-0.63	-0.52	-0.41	-5.17	-3.79	-2.86	-2.15
Size 3	-1.14	-0.78	-0.63	-0.49	-4.16	-3.19	-3.08	-2.22
Big	-1.29	-0.79	-0.35	0.19	-4.31	-2.92	-1.39	0.62
	b (Market)				**t(b)** ($h_0 = 1$)			
Small	0.93	0.98	0.98	0.98	-2.64	-0.88	-1.07	-0.92
Size 2	1.00	1.00	1.02	1.03	0.00	0.00	0.93	1.32
Size 3	1.02	1.02	1.09	1.08	0.62	0.69	3.73	3.09
Big	1.01	1.01	1.02	0.92	0.28	0.31	0.68	-2.22
	s (Size)				**t(s)**			
Small	1.31	1.21	1.19	1.16	32.24	34.87	41.43	34.79
Size 2	1.14	1.07	1.09	1.08	31.21	35.42	33.09	30.79
Size 3	0.88	0.86	0.90	0.85	17.63	19.38	24.27	21.28
Big	0.42	-0.02	0.00	-0.21	7.81	-0.44	-0.05	-3.76

Adjusted R-Squared

	Low	B/M 2	B/M 3	High
Small	0.94	0.96	0.97	0.96
Size 2	0.95	0.96	0.96	0.95
Size 3	0.90	0.92	0.95	0.94
Big	0.86	0.86	0.88	0.80

Table 3.32: Regressions of the 16 value-weighted Size-B/M sorted portfolios; January 2000 to March 2015. At the end of each month, four size (from small to big) intervals and four B/M (from low to high) intervals are determined independently. Stocks that fit each of the total 16 resulting intervals are formed as portfolios. We take their monthly excess returns as the LHS variable in the regression. The RHS variables of the regressions are the three factors from factor set 5 (shown in Table 3.5) including a market factor, a size factor and a HML factor.

$$R_{i,t} - R_{F,t} = a_i + b_i(R_{M,t} - R_{F,t}) + s_i SMB_t + h_i HML_t + e_{i,t}$$

Factor set 5 Three-factor model

	Low	B/M 2	B/M 3	High	Low	B/M 2	B/M 3	High
		a (Intercept)				**t(a)**		
Small	-0.56	-0.38	-0.19	-0.26	-2.45	-1.96	-1.19	-1.40
Size 2	-0.92	-0.54	-0.51	-0.63	-4.57	-3.23	-2.73	-3.52
Size 3	-0.79	-0.54	-0.66	-0.77	-3.20	-2.32	-3.17	-3.90
Big	-0.75	-0.35	-0.60	-0.43	-3.26	-1.58	-2.52	-2.06
		b(Market)				**t(b)** ($h_0 = 1$)		
Small	0.92	0.98	0.98	0.98	-3.07	-0.88	-1.06	-0.94
Size 2	0.99	0.99	1.02	1.04	-0.43	-0.52	0.92	1.92
Size 3	1.00	1.01	1.09	1.10	0.00	0.37	3.72	4.33
Big	0.99	0.99	1.03	0.95	-0.38	-0.39	1.09	-2.06
		s (Size)				**t(s)**		
Small	1.26	1.23	1.20	1.22	28.04	31.65	37.37	33.25
Size 2	1.09	1.03	1.09	1.17	27.09	30.92	29.26	32.72
Size 3	0.72	0.76	0.91	0.97	14.63	16.21	21.95	24.63
Big	0.19	-0.21	0.11	0.06	4.12	-4.76	2.28	1.48
		h (B/M)				**t(h)**		
Small	-0.13	0.06	0.04	0.14	-2.34	1.20	0.97	3.14
Size 2	-0.14	-0.11	-0.01	0.25	-2.86	-2.67	-0.29	5.85
Size 3	-0.39	-0.27	0.04	0.32	-6.66	-4.90	0.78	6.93
Big	-0.61	-0.49	0.29	0.71	-11.27	-9.43	5.14	14.27

R Square

	Low	B/M 2	B/M 3	High
Small	0.94	0.96	0.97	0.96
Size 2	0.95	0.97	0.96	0.96
Size 3	0.92	0.93	0.95	0.95
Big	0.92	0.91	0.90	0.91

Table 3.33: Regressions of the 16 value-weighted Size-B/M sorted portfolios; January 2000 to March 2015. At the end of each month, four size (from small to big) intervals and four B/M (from low to high) intervals are determined independently. Stocks that fit each of the total 16 resulting intervals are formed as portfolios. We take their monthly excess returns as the LHS variable in the regression. The RHS variables of the regressions are the five factors from factor set 5 (shown in Table 3.5) including a market factor, a size factor, a HML factor, a return on asset factor (RMW) and an investment style factor (CMA).

$$R_{i,t} - R_{F,t} = a_i + b_i(R_{M,t} - R_{F,t}) + s_i SMB_t + h_i HML_t + r_i RMW_t + c_i CMA_t + e_{i,t}$$

Factor set 5 Five-factor model

	Low	B/M 2	B/M 3	High	Low	B/M 2	B/M 3	High
	a (Intercept)				**t(a)**			
Small	-0.28	-0.29	-0.10	-0.22	-1.25	-1.42	-0.59	-1.15
Size 2	-0.70	-0.47	-0.52	-0.65	-3.47	-2.74	-2.79	-3.48
Size 3	-0.62	-0.51	-0.64	-0.65	-2.57	-2.18	-3.04	-3.16
Big	-0.59	-0.44	-0.52	-0.47	-2.48	-1.93	-2.14	-2.15
	b(Market)				**t(b)** ($h_0 = 1$)			
Small	0.90	0.97	0.97	0.98	-3.89	-1.29	-1.57	-0.92
Size 2	0.97	0.99	1.02	1.04	-1.30	-0.51	0.94	1.87
Size 3	0.99	1.01	1.09	1.08	-0.36	0.37	3.74	3.43
Big	0.97	1.00	1.02	0.96	-1.11	0.00	0.72	-1.59
	s (Size)				**t(s)**			
Small	0.93	1.12	1.10	1.18	10.88	14.52	17.17	16.09
Size 2	0.83	0.95	1.11	1.20	10.69	14.55	15.56	16.73
Size 3	0.53	0.73	0.89	0.82	5.76	8.12	11.13	10.51
Big	-0.01	-0.11	0.02	0.11	-0.07	-0.12	0.22	1.31
	h (B/M)				**t(h)**			
Small	-0.16	0.04	0.02	0.13	-3.13	0.90	0.63	2.97
Size 2	-0.16	-0.12	-0.01	0.25	-3.55	-2.97	-0.33	5.82
Size 3	-0.42	-0.28	0.03	0.31	-7.50	-5.15	0.68	6.55
Big	-0.63	-0.48	0.28	0.71	-11.68	-9.13	4.96	14.14
	r (Profitability)				**t(r)**			
Small	-0.42	-0.09	-0.10	-0.01	-4.53	-1.12	-1.43	-0.12
Size 2	-0.30	-0.04	0.13	0.07	-3.58	-0.50	1.61	0.86
Size 3	-0.09	0.09	0.08	-0.16	-0.85	0.88	0.91	-1.85
Big	-0.21	0.08	-0.02	0.08	-2.18	0.80	-0.16	0.92
	c (Investment style)				**t(c)**			
Small	0.09	0.16	0.14	0.13	0.96	1.92	2.08	1.70
Size 2	0.15	0.21	0.27	0.09	1.87	2.99	3.55	1.16
Size 3	0.49	0.34	0.29	0.13	5.02	3.61	3.46	1.59
Big	0.14	-0.19	0.30	0.05	1.50	-2.05	3.04	0.61

R Square

	Low	B/M 2	B/M 3	High
Small	0.95	0.96	0.97	0.96
Size 2	0.96	0.97	0.96	0.96
Size 3	0.93	0.93	0.95	0.95
Big	0.92	0.91	0.90	0.91

Table 3.34: The average adj R^2s for the 2, 3 and 5 -factor models produced by the 5 sets of factors specified in Table 3.5.

The Average adjusted R^2s			
	2 factor model	3 factor model	5 factor model
Factor Set 1	92.31%	94.46%	94.65%
Factor Set 2	92.25%	93.54%	94.29%
Factor Set 3	92.50%	94.27%	94.73%
Factor Set 4	91.56%	93.35%	93.62%
Factor Set 5	92.25%	94.00%	94.27%

3.1.7 GRS Tests Results and Discussion

Table 3.35 shows the GRS statistics for the 15 models. The *GRS* tests are the joint F test to test the hypothesis that the intercepts are jointly zero (see also Section 2.4.2 for more explanation of the *GRS* test). Therefore, the higher the *GRS* test, the less likely it is that the intercepts are jointly zero. As shown in the table, all of the *GRS* results (also the F values of the joint F-tests) are greater than 0.98, with the highest and the lowest p-value of 0.43 and 0.17. This means the *GRS* tests reject the hypothesis that the intercepts are jointly zero. Even though the *GRS* tests reject all the models we tested here, we can still use it to compare the performance of the 15 different models.

The five-factor models perform better than the two- and three- factor models judged by GRS tests

Comparing the two-, three-, and five-factor models constructed using the five sets of factors, we can say that the five-factor model consistently outperforms the two- and three- factor model. Taking factor set 1 as an example, there are improvements from the two-factor model to the three-factor model, and from the three-factor model to the five-factor model: the two-factor model has a *GRS* score of 1.75 and a p-value of 0.18; the three-factor model has a *GRS* score of 1.36 and p-value of 0.26; and finally, the five-factor model has a *GRS* score of 1.14 and p-value of 0.34. This is caused by the fact that the two extra factors (RMW and CMA) are constructed by weighting against the size variable only; there is less influence from the HML factor which is highly correlated with RMW and CMA (see panel B of Tables 3.10 to 3.14). Among the 15 models, the one that has the lowest *GRS* score is the five-factor model created by factor set 3 with a *GRS* score of 0.98 (see Table 3.5 for factor set 5 construction).

The absolute intercepts

Of all the factor sets, the five-factor model produces consistently smaller absolute intercepts than the two- and three-factor models. This phenomenon is consistent with the result found by the regression analysis that five-factor models produce smaller intercepts than three-factor models.

We use the two ratios specified in Fama and French (2015) to test the distributions of excess returns left unexplained by the model. The first ratio is $A|a_i|/A|\overline{r}_i|$ and the second ratio $A(\widehat{\alpha}_i^2)/A(\widehat{\mu}_i^2)$

Apart from judging the intercepts of regressions, we also use two ratios to learn the properties of dispersion distribution of excess returns of the LHS portfolios left unexplained by the model. The first ratio is A$|a_i|$/A$|\overline{r}_i|$ and the second ratio is A$(\widehat{\alpha}_i^2)$/A$(\widehat{\mu}_i^2)$. The first ratio in column 4 of Table 3.35 is the ratio of average absolute value of the intercepts over the average absolute value of the LHS portfolios' deviation from their cross-sectional average. $\overline{r}_i$=$\overline{R}_i$-$\overline{R}$, $\overline{R}_i$ is the time series average return on portfolio i, and $\overline{R}$ is the grand average of LHS portfolio's excess returns. This ratio tells us how big is the deviation of the regression intercepts are compare with the overall LHS portfolios' deviations. So from looking at column 4, we can say that for all models, this ratio ranged from 0.31 to 0.65. Since we would prefer the model to have as small an A$|a_i|$ as possible, the best model in terms of the A$|a_i|$/A$|\overline{r}_i|$ ratio is the five-factor model constructed using of factor set 3, with a value of 0.31 (Table 3.35).

The second ratio is $A(\widehat{\alpha}_i^2)/A(\widehat{\mu}_i^2)$. It estimates the proportion of the variance of LHS expected returns left unexplained by the model. α_i=a_i-e_i and $\mu_i = \overline{r}_i - e_i$. a_i is the intercept estimated by our regression model, then the true (unknown) intercept is defined as α_i. $a_i = \alpha_i + e_i$. Similarly, $\overline{r}_i$ is the estimated portfolio

i's expected deviation from the grand mean of all portfolios, and the true portfolio i's deviation is defined as μ_i. $\bar{r}_i = \mu_i + e_i$. The cross-sectional average of μ_i is zero, so $A(\mu_i^2)$ is the cross- sectional variance of expected portfolio returns and $A(\alpha_i^2)/A(\mu_i^2)$ is the proportion of $A(\mu_i^2)$ left unexplained by the model. Further more, $E(a_i^2) = \alpha_i^2 + E(e_i^2)$ (α_i is a constant). The estimated $\widehat{\alpha}_i^2$ of α_i^2 is $E(\widehat{a}_i^2) - E(e_i^2)$. Similary, $E(\bar{r}_i^2) = \widehat{\mu}_i^2 + E(e_i^2)$, ($\mu_i$ is a constant). The estimated $\widehat{\mu}_i^2$ of μ_i^2 is $E(\mu_i^2) - E(e_i^2)$. $\widehat{\mu}_i^2 = E(\mu_i^2) - E(e_i^2)$. Therefore, the ratio $A(\widehat{\alpha}_i^2)/A(\widehat{\mu}_i^2)$, then, estimates the proportion of the variance of LHS expected returns are left unexplained. The values of the ratio are quite high for all models, which indicates that none of the models explain fully the variations in portfolio returns. Since, again, the smaller the ratio, the better the model, the model shows the best $A(\widehat{\alpha}_i^2)/A(\widehat{\mu}_i^2)$ (with a value of 0.11) is the five-factor model using factors set 3.

3.1.8 Regression and *GRS* Tests Conclusion

Throughout this study, we have been using two measurements to judge how well the right-hand-side factors explain the left-hand-side portfolios returns; these are adjusted-R_2 and the GRS score. These two measurements judge a model's performance from two perspectives: adjusted-R_2 captures how well the data fits a regression line, while the GRS tells us whether the regressions' intercepts are jointly zero. Alternatively, we want a model to have a combined high adjusted-R_2 and low GRS score. We do not take a strong stand on which measure is the ultimate one to pick our final model, but rather we use them to compare the relative performance of a number of models.

Surprisingly, although we do not expect the two measures will give the same conclusion on which model is the best, yet both the GRS test (Table 3.35) and the adjusted-R_2 (Table 3.34) indicate that the best model is the five-factor model produced by factor set 3. At this point, we conclude that the best model is, however, a two-factor model containing a market factor and a size factor. We discard the remaining three factors in our model for the following two reasons: first, the RMW and the CMA each has low explanatory power in the model; and second, the HML factor is highly correlated with the strong SMB factor.

In the next section, we will move a step further, and investigate whether the determinants of breakpoints would fundamentally influence a model's performance by systematically changing a factor's breakpoints and then observe the subsequent performance of the model.

Table 3.35: Summary statistics for tests of three and five-factor model: January 2000 to March 2015. The test scores reveals the ability of the RHS factors as a set explain the LHS monthly excess retruns of the 16 mimicking portfolios. The *GRS* test scores tell to what extent the model regressions' intercepts are jointly zero; the A$|a_i|$ is the absolute value of the intercepts; the first ratios A$|a_i|$/A$|\overline{r}_i|$ is the average absolute value of intercepts over the average absolute value of $\overline{r}_i$ where $\overline{r}_i$ is the average return on portfolio i minus the average of all portfolio returns; and A$(\widehat{\alpha}_i^2)$/A$(\widehat{\mu}_i^2)$ is the A(α_i^2)/A$(\overline{r}_i^2)$ corrected for sampling errors.

	GRS	A$\|a_i\|$	A$\|a_i\|$/A$\|\overline{r}_i\|$	A$(\widehat{\alpha}_i^2)$/A$(\widehat{\mu}_i^2)$
Factor Set 1 Two-factor model	1.75 p-value 0.18	0.004	0.65	0.47
Factor Set 1 Three-factor model	1.36 p-value: 0.26	0.003	0.44	0.18
Factor Set 1 Five-factor model	1.14 p-value 0.34	0.002	0.36	0.14
Factor Set 2 Two-factor model	1.70 p-value 0.19	0.004	0.64	0.47
Factor Set 2 Three-factor model	1.21 p-value 0.31	0.003	0.45	0.20
Factor Set 2 Five-factor model	1.05 p-value 0.39	0.002	0.36	0.13
Factor Set 3 Two-factor model	1.62 p-value 0.20	0.004	0.64	0.48
Factor Set 3 Three-factor model	1.06 p-value 0.37	0.003	0.39	0.14
Factor Set 3 Five-factor model	0.98 p-value 0.43	0.002	0.31	0.11
Factor Set 4 Two-factor model	1.81 p-value 0.17	0.004	0.59	0.41
Factor Set 4 Three-factor model	1.41 p-value 0.24	0.003	0.39	0.16
Factor Set 4 Five-factor model	1.41 p-value 0.23	0.003	0.38	0.14
Factor Set 5 Two-factor model	1.77 p-value 0.18	0.004	0.57	0.37
Factor Set 5 Three-factor model	1.28 p-value 0.29	0.003	0.40	0.16
Factor Set 5 Five-factor model	1.20 p-value 0.31	0.002	0.36	0.16

3.2 Sensitivity Analysis 2: Finding the Optimal Breakpoints

3.2.1 Introduction

In the studies of the creation and application of the classic asset pricing factor models, factors' definitions as well as variables' breakpoints have always been taken as given. For example, in the Fama and French (2015), the SMB factor was determined as small minus big where the breakpoint for size was the 50^{th} percentile of stocks in the NYSE by capitalization. Similarly, the HML breakpoints were the 30^{th} and 70^{th} percentile of the stocks in the NYSE by B/M. Various breakpoints were tested and the conclusion was that breakpoints were negligible for the study of the US market (Fama and French, 1993).

However, those breakpoints were untested and should be tested in China. Because in China, businesses follow a vastly different business growth model than in the US market. For example, in China the government owns some of the large companies. Once the companies are owned by the government, the function of their business will differ from those which are owned privately (Gul et al., 2010). Also, a government-owned company would have more access to resources and face less government constrains, while a privately owned firm may face tougher regulations and less access to resources. This means that firms' characteristics may differ dramatically among, for example, small firms. Therefore, a 50%–50% breakpoint may not able to separate the size characteristics effectively. A different break point may be more appropriate. Finally, as shown in Table 3.20, the adjusted R^2 for the big stocks portfolios are on average much lower than the rest of the portfolios. This lead us to believe there is a pattern in the big stocks that seemed unique to the big-stock portfolios only. Thus, testing a different breakpoint makes it appropriate to investigate whether these unique characteristics can be captured.

Therefore, in this section, we conduct a systematic examination of the SMB and HML by using systematically different break points to investigate whether defining factors differently this way will statistically change the models' explanatory power. Once the factors are reconstructed this way, we will test them on two models: a two-factor model containing a market and a size factor, and a five-factor model containing a market, a size, a book-to-market factor, an investment style factor, and a profitability factor. Note that the investment style factor (CMA) and the profitability factor (RMW) of Fama and French (2015) are not breakpoint-tested in this chapter because they were not significant, as already shown in Chapter 2. So in the five-factor model, we will change the breakpoints of the size (SMB) and the book-to-market (HML) factor simultaneously and investigate whether any combination of these two factors would increase models' explanatory power significantly. The models' explanatory power will be indicated by the adjusted R^2s and the GRS tests.

In testing the two-factor model, we reconstruct the size factor (SMB) by assigning size break points of 10%, 20%, 30%, 40%, 50%, 60%, 70%, 80%, and 90%. The other factor – the market factor – will stay unchanged. Therefore, total nine pairs of factors will be tested using the two-factor model.

In testing the five-factor model, we reconstruct simultaneously the size factor (SMB) and the book-to-market factor by assigning size break points of 10%, 20%, 30%, 40%, 50%, 60%, 70%, 80%, 90%, and assigning book-to-market factor (HML) break points of 10% – 50%, 20% – 60%, 30% – 70%, and 40% – 80%. Therefore, 36 sets of factors (9×4) will be tested on the three-factor model.

This test is crucial for especially the Chinese market, because an inappropriate size or book-to-market break point could result in the choice of an inappropriate model and when such an asset pricing model is used to analyze mutual fund performance, a misleading conclusion could be derived.

3.2.2 The Results and Discussion

Results of the two-factor model

Table 3.36 shows the results from testing the different breakpoints on a two-factor model. As can be seen, there are some difference in the adjusted R^2s, especially when the breakpoint moves from 10% to 20% (the R^2 went up from 89.38% to 92.16%). From a breakpoint of 20% to 90%, there is no large difference in adjusted R^2, even-though the best break point is at 60%, with an adjusted R^2 of 93.50%. The fact is that the R^2 picked at the 60% breakpoint is somewhat consistent with the regression result discussed previously (see Table 3.19 as an example). The big-stock portfolios have on average smaller R^2s, which led us to believe there are unique patterns in the big-stock portfolios. The fact that the breakpoint moves to 60% may reduce the effect of this pattern, and hence ease the problem embedded in the big-stock portfolios.

The *GRS* tests show a slightly different patterns. Since the *GRS* test tests whether the intercepts of the regressions are jointly zero, which is the preferred outcome, the best breakpoint in terms of the *GRS* test is the point of 20%.

Table 3.36: Performance of the two-factor model defined by different size breakpoints.

Size breakpoints	R^2	**GRS**
10% small 90% big	89.38%	1.81
20% small 80% big	92.16%	1.76
30% small 70% big	92.75%	1.82
40% small 60% big	93.17%	1.80
50% small 50% big	93.39%	2.01
60% small 40% big	93.50%	2.18
70% small 30% big	93.43%	2.23
80% small 20% big	93.18%	2.39
90% small 10% big	92.61%	2.75

Results of the five-factor mode

Table 3.37 shows the total 36 combinations to define the size and HML factors as a pair. Recall that we do not worry about assigning different breakpoints for the RMW and CMA factors. We keep the breakpoint for size at 50% and for B/M at 30% – 70% when constructing RMW and CMA factors if size and HML factors are involved, since RMW and CMA factors are not as strong as the size and HML factors in explaining stock return variations, as indicated in the regression analysis and the *GRS* tests.

As shown in Table 3.37, assigning different breakpoints for size and B/M ratio creates slightly different explanatory power measured by the average R squares. There is very little difference in the models' explanatory power when the size breakpoints are 40%, 50%, 60% , 70%, 80% or 90%. Also, for B/M ratio, except for the breakpoints of 10% – 50%, different breakpoints make very little difference in models' explanatory power. The best breakpoint combination is for the size breakpoint to be 70% and for the B/M breakpoints to be 30% and 70%, which produces an average R square of 94.88% for the five-factor model. These characteristics are more clearly shown in Figure 3.3. This combination of best breakpoint gives us two hints: firstly, since there are uncommon patterns in the big-stock portfolios, it seemed more appropriate to move the size breakpoint up (to 70% in this case). Secondly, the optimal breakpoint for B/M of 30% and 70% proposed by Fama and French (1993) and Fama and French (2015) may come from their preliminary testing, even though the process of how these breakpoints were decided was not mentioned in their papers.

The conclusion reflected by the *GRS* tests are, however, different. As shown in Table 3.38, assigning different breakpoints to size and B/M ratio generates vastly different *GRS* scores. The *GRS* scores increase dramatically when size breakpoints are changed from low to high (from 10% to 90%). Since the lower the *GRS* score, the better the performance of the model, we can say that fixing the breakpoint for size at 20% allows us to construct the best size factors. With each size breakpoint change, the pattern of the *GRS* scores is not affected much by changing the breakpoints for the B/M ratio; apart from a B/M breakpoint of 40% – 80%, the different B/M breakpoints permit similar model exlanatory powers. This phenomenon is more clearly expressed in a graph in Figure 3.4.

Figure 3.4 is the graphically representation of the Table 3.38 which shows the *GRS* test scores produced by the five-factor model, with different intervals for the size and the B/M variables used in the double-sorting process. Recall that for a good-fitted model with low intercepts, we want the *GRS* score to be as low as possible. The figure shows the best models judged by the *GRS* scores are those on the left-bottom corner of the graph. The intervals for these particular models are B/M 30% to 70% (same as Fama and French (1993, 2015)), or 20% to 60%, or 10% to 50%. As for the size intervals, they are 10% small 90% big, or 20% small 80%big, or 30% small 70% big – which are different from the 50% small 50% big in Fama and French (1993, 2015).

Table 3.37: The Adjusted R-Squared of the five-factor models formed with factors set 5. Within the factor set 5, different breakpoints are used to define the size and B/M variables. Therefore, a total of 36 pairs of size and B/M factors are created, which produced essentially 36 slightly different sets of factors regardless the fact that factor construction method used are the same (factor construction method 5). The breakpoints for the RMW and CMA factor are unchanged for simplicity.

Breakpoints	**B/M 10%-50%**	**B/M 20%-60%**	**B/M 30%-70%**	**B/M 40%-80%**
10% small 90% big	91.22%	91.90%	92.47%	92.18%
20% small 80% big	92.78%	93.53%	93.91%	93.78%
30% small 70% big	93.28%	94.08%	94.37%	94.26%
40% small 60% big	93.66%	94.33%	94.60%	94.51%
50% small 50% big	93.76%	94.47%	94.79%	94.71%
60% small 40% big	93.92%	94.52%	94.83%	94.73%
70% small 30% big	93.99%	94.59%	94.88%*	94.73%
80% small 20% big	93.99%	94.46%	94.71%	94.59%
90% small 10% big	93.27%	93.59%	94.09%	93.94%

Figure 3.3: The visualization of Table 3.37 Performance of the winning model in the form of Adjusted R Squares: January 2000 to March 2015. The Adjusted R-Squared of the five-factor models formed with factors set 6. Within the factor set 6, different breakpoints are used to define the size and B/M variables. Therefore, a total of 36 pairs of size and B/M factors are created, which procuded essentially 36 slightly different sets of factors regardless the fact that factor construction method used are the same (factor construction method 6). The breakpoints for the RMW and CMA factor are unchanged for simplicity.

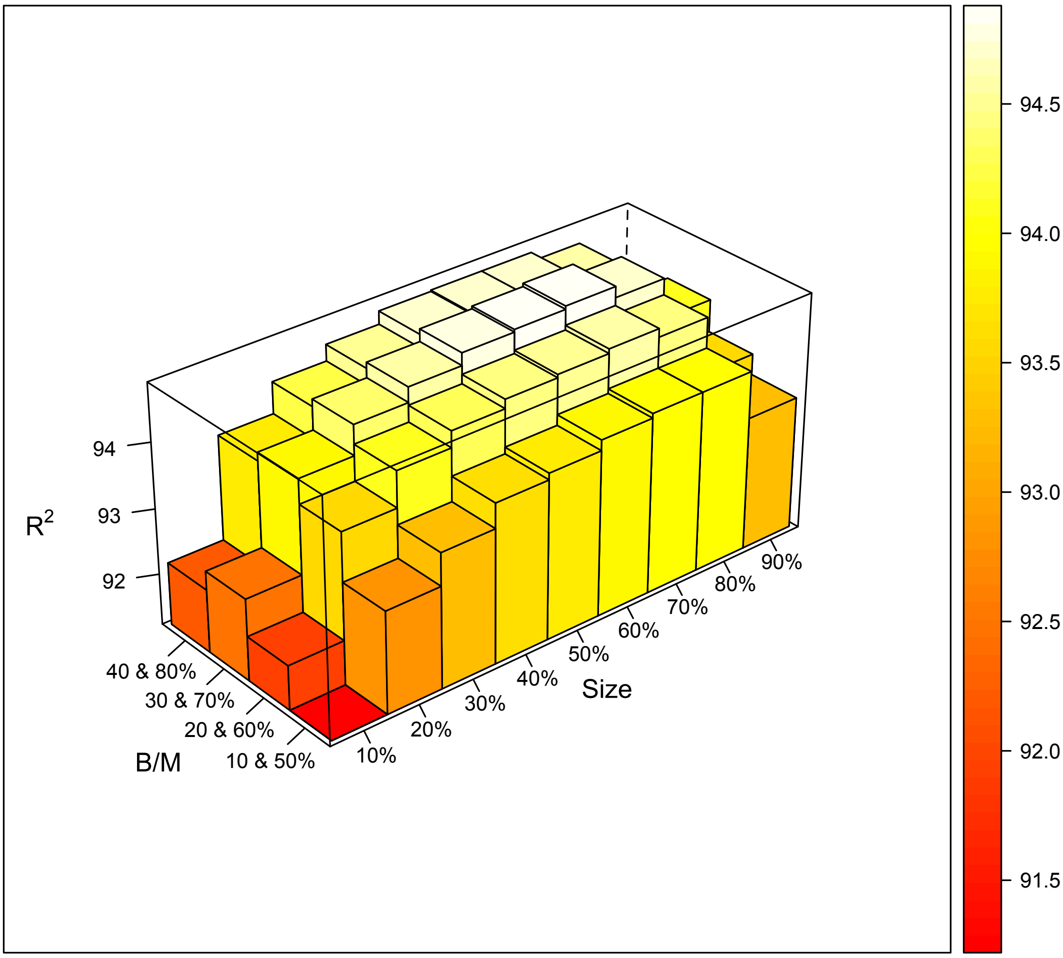
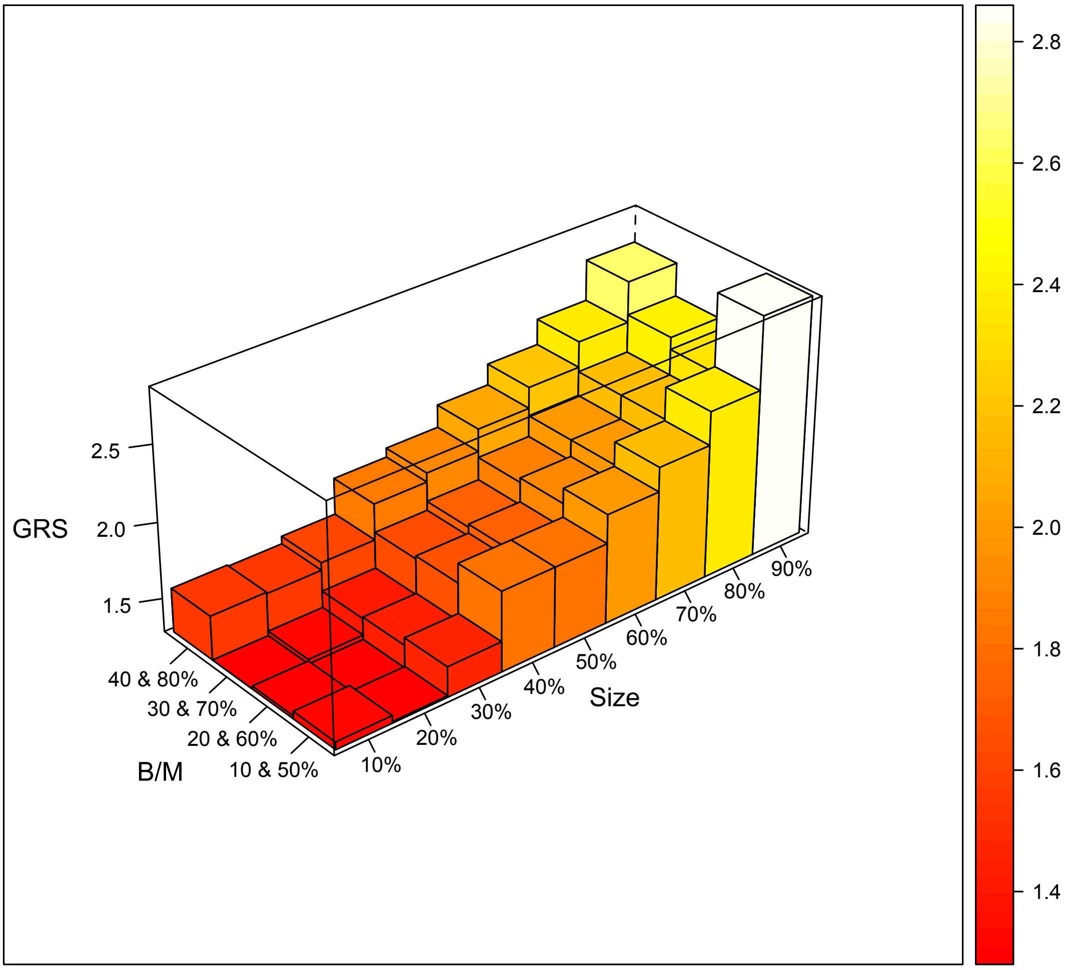


Table 3.38: Performance of the winning model in the form of the GRS test: January 2000 to March 2015. The GRS tests of the five-factor models formed with factors set 5. Within the factor set 5, different breakpoints are used to define the size and B/M variables. Therefore, a total of 36 pairs of size and B/M factors are created, which procuded essentially 36 slightly different sets of factors regardless the fact that factor construction method used are the same (factor construction method 5). The breakpoints for the RMW and CMA factor are unchanged for simplicity.

Size Breakpoints	**BM 10%-50%**	**BM 20%-60%**	**BM 30%-70%**	**BM 40%-80%**
10% small 90% big	1.33	1.30	1.28*	1.57
20% small 80% big	1.29	1.28*	1.31	1.56
30% small 70% big	1.48	1.43	1.42	1.61
40% small 60% big	1.81	1.68	1.66	1.85
50% small 50% big	1.81	1.74	1.72	1.91
60% small 40% big	2.00	1.90	1.87	2.06
70% small 30% big	2.16	2.01	2.01	2.20
80% small 20% big	2.38	2.71	2.17	2.37
90% small 10% big	2.86	2.34	2.42	2.64

Figure 3.4: Visualization of Table 3.38. Performance of the winning model in the form of the GRS test: January 2000 to March 2015. The GRS tests of the five-factor models formed with factors set 5. Within the factor set 5, different breakpoints are used to define the size and B/M variables. Therefore, a total of 36 pairs of size and B/M factors are created, which procuded essentially 36 slightly different sets of factors regardless the fact that factor construction method used are the same (factor construction method 5). The breakpoints for the RMW and CMA factor are unchanged for simplicity.



3.2.3 Section Conclusions

In this section (Section 3.2), we analyzed the performance of a two-factor model (market factor plus size factor) and a five-factor model of Fama and French (2015) using the stock return data in the Chinese stock markets.

We found the way the factors are constructed had little effect on the models' performance, while different values of breakpoints for size and B/M ratio do make some difference to the models' performance. In other words, how to define size becomes dominant regardless of how other factors are weighted into the factors.

3.3 Chapter Discussion and Conclusions – An Alternative Multi-Factor Model for China

We began our journey by suspecting that since the Chinese stock market has such a specific characteristics, factors in the traditional asset pricing models, such as the Fama and French three-factor model, may need to be reconstructed to reflect these characteristics for the models to work better. We ended in taking two steps to investigate this question. In the first step or the first sensitivity analysis, we designed and investigated a total of five sets of factors which used different weightings against other factors in the factor calculation process. We found the five sets of factors provided a similar description of average returns of the 16 portfolios on the right-hand-side. If we have to pick a best model of of all models examined, the five-factor model, which consists of factor set 1, generated the highest average R^2 of 94.46%, but it was the five-factor model using factor set 2 that produced the lowest GRS score of 0.98.

In the second stage or sensitivity analysis, we looked at whether assigning different breakpoints to the variables produced significantly statistically different explanation power of the models. We examined the two- and five-factor models produced by using varying breakpoints for SMB and HML and found that using 70% as a breakpoint for size (70% small, 30% big) to define the SMB factor, and 30% and 70% for the B/M ratio to define the HML factor produced the highest adjusted R^2 of 94.88%. In other words, the size breakpoint is different from that of the US market, while the best B/M breakpoints are the same for the Chinese and the US markets.

Therefore, the conclusion is that the ways the factors were constructed matters very little to the models' explanation power, while different breaking points make some difference to the factors' explanation power.

The next important question is: In the places where the traditional factor asset pricing models are applied, would using a two-, a three-, or a five-factor model produce fundamentally different results, for example, in mutual fund performance analysis? In the next chapter, we will find the answer to this question.

4. Performance Analysis of the Chinese Equity Mutual Funds

4.1 Introduction

The topic of Chinese mutual fund performance evaluation has been attracting more and more attention from scholars and investment institutions around the world, especially since the tremendous growth rate of this industry over the last 20 years was revealed (Song, 2015; Pan and Mishra, 2018). By the first quarter of 2015, the size of the Chinese mutual fund industry had grown to $USD 708,884 million from $USD 13 million in 1998–an over 190% compounded annual growth rate for the last 17 years. Although there are not a large number of studies that focus on the performance and characteristics of this industry, the number of such studies has been growing in the last few years, especially since 2013. The list below provides a picture of the various studies appearing in the last few years which tried to study the Chinese mutual funds more thoroughly:

Song (2015) reported that besides the investment banks, the mutual fund industry is another hot spot for joint venture and other corporate manifestations. Chen (2013) used indices as benchmarks and reported that mutual fund managers in China have stock- selection abilities but not market-timing abilities. Feng and Johansson (2015) investigated the effect of purchasing IPOs on mutual fund performance and reported funds with higher residual funds[1] showed higher performance. Gong et al. (2016) studied the relationship between the size of the top shareholder and the the fund performance, and reported that multiple large shareholders reduced the fund performance. Rao et al. (2017) reported that the Chinese mutual funds are able to provide higher returns than the market and their managers possess market-timing ability. Su et al. (2012) reported that there is no evidence of long-term persistence in the Chinese mutual fund industry. Shi (2013) reported that on average firms are able to beat the market, as revealed by the positive Jensen's α. In a somewhat related study, Feng et al. (2014) investigated Chinese investors' ability to invest in potentially high-performing mutual funds, and they reported that Chinese investors have no mutual fund selection-ability.

Among these studies, there was evidence that funds' performance is inconsistent. For example, (Su et al., 2012) claimed that funds under perform and outperform the market under different macro-market conditions; Kiymaz (2015) reported that Chinese funds do not consistently provide excess returns and show great variations in returns. However, the majority of the studies reported that the Chinese mutual funds do have stock-selection ability (Chen, 2013; Rao et al., 2017; Shi, 2013).

The most popular asset pricing model used in mutual fund analysis are the CAPM, the Fama and French three-factor model. In Chapter 2, We studied a large number of combination of factors for China and concluded that a two-factor model containing the market factor and a size factor best explains the stock return variations in China.

Therefore, in this study, instead of using only one model or examining data in only one period, we investigate mutual funds' performance using various different

[1]A residual fund is the initial mutual funds' buying in the IPO market.

asset pricing models and within different time periods. We believe, the performance inconsistency, as least in part, comes from the use of the various different models.

4.2 Data on the Chinese Mutual Funds

4.2.1 The Mutual Fund Returns

To study the performance of the Chinese mutual funds, we firstly collected funds' monthly price data from the Bloomberg database and constructed individual funds' monthly returns as our final dataset to use in our analysis. The period of the data was December 2007 to December 2016, a total of 109 months. The total number of mutual funds was 287. We collected mutual funds' monthly prices from the Bloomberg database with the following criteria:

1. Funds' market status includes active and inactive funds. We collected funds that are both live and dead to avoid survivorship bias.
2. Funds belong to a primary share class.
3. Funds' country of domicile is China.
4. Funds' investment objective[2] is equity market.

The survivorship bias influences the absolute performance measure significantly. Otten and Bams (2002) compared the mean of survivorship biased and survivorship-biased-free data and found the two data sets were significantly different: excluding the dead funds would result in an overestimation of average return by as high as 0.45% per year. Most studies (Fama and French, 1993; Carhart, 1997; Otten and Bams, 2002) used survivorship-biased-free data in their studies.

[2]This is Bloomberg's term for funds' characteristics

Our data do not seem to include dead funds, regardless of the fact that we included both active and inactive funds[3]. This, however, may not affect our results severely because instead of examining individual funds' absolute performance, we are interested in comparative performance determined by four different models.

4.2.2 The Asset Pricing Model as Benchmarks

A two-factor models as primary model

Based on the previous examinations in Chapter 2, we concluded that the two-factor model containing a market and a size factor (Equation 4.1) is the most appropriate model (among the CAPM, the Fama and French three- and five-factor models) for the Chinese stock market. Therefore, this model will be used as our primary model to conduct the mutual fund analysis as below. The details of this model and the explanation of variables are in Chapter 2 and will not be discussed again here. Since the breakpoint and construction method did not affect the models' explanatory power dramatically, we will use the most popular construction 1 (in Table 3.5) to create the SMB factor.

$$E[R_i] - R_f = \alpha_i + \beta_1(R_M - R_f) + \beta_2 SMB_t + e_{i,t} \tag{4.1}$$

Other Factor models used as a comparison

We will also use an additional popular four models (Equations 4.2 to 4.5) to analyze our funds' performance. We do this to compare the results derived from the two-factor model above.

[3]When collecting the mutual funds data using the Bloomberg terminal, we restricted the data search to include both active and inactive funds. However, the search indicated there were only two dead funds – the difference in the number of funds was two when we searched for active and inactive fund together, and searched the active funds only.

These additional four models are: the CAPM (Equation 4.2); a two-factor model containing market and HML factors (Equation 4.3); a Fama and French three-factor model (Fama and French, 1993) (Equation 4.4) and finally, a Fama and French five-factor model (Fama and French, 2015) (Equation 4.5).

$$E[R_i] - R_f = \alpha_i + \beta(R_M - R_f) + e_{i,t} \tag{4.2}$$

$$E[R_i] - R_f = \alpha_i + \beta_1(R_M - R_f) + \beta_2 HML_t + e_{i,t} \tag{4.3}$$

$$E[R_i] - R_f = \alpha_i + \beta_1(R_M - R_f) + \beta_2 SMB_t + \beta_3 HML_t + e_{i,t} \tag{4.4}$$

$$E[R_i] - R_f = \alpha_i + \beta_1(R_M - R_f) + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 RMW_t + \beta_5 CMA_t + e_{i,t} \tag{4.5}$$

The method of factor construction in each model

Below are the construction methods used in each of the models examined:

The factors in the two-factor model: the market and the size factor: The proxy for the risk-free rate is the China three-month interbank loan rate (monthly frequency), and the market portfolio (as a proxy) is the Shanghai Composite Index 300 (SCI300) monthly returns. The SMB is the factor constructed using method 1 in Table 3.5.

The factor in the CAPM: The proxy for the risk-free rate is the China three-month interbank loan rate (monthly), and the market portfolio (as a proxy) is the Shanghai Composite Index 300 (SCI300) monthly returns.

The factors in the two-factor model: a market and a HML factor: The proxy for the risk-free rate is the China three-month interbank loan rate (monthly frequency), and the market portfolio (as a proxy) is the Shanghai Composite Index 300 (SCI300) monthly returns. The HML factor is constructed using factor construction method 1 in Table 3.5.

The factors used in the Fama French three-factor model: The proxy for the risk-free rate is the China three-month interbank loan rate (monthly frequency), and the market portfolio (as a proxy) is the Shanghai Composite Index 300 (SCI300) monthly returns. The SMB and HML are constructed using factor construction method 1 in Table 3.5.

The factors used in the Fama French five factor model: Again, the proxy for the risk-free rate is the China three-month interbank loan rate (monthly frequency), and the market portfolio (as a proxy) is the Shanghai Composite Index 300 (SCI300) monthly returns. The SMB, HML, RMW and CMA are constructed using factor construction method 1 in Table 3.5.

Table 4.1 shows the market factor has the lowest return (-0.002 per month) and the highest standard deviation. The correlation between the market factor and the SMB, and the market factor and HML are low (0.045 and 0.08 respectively). However, the correlation between the SMB and HML is still high at 0.36, which makes it difficult to believe that the three factors combined makes an appropriate model for the Chinese market. The CMA has a low correlation with the market factor; however, it has a high one with the SMB factor; the RMW also has a high correlation with all the other four factors. This gives us a hint that both the CMA and the RMW factor may not be appropriate to combine with the market factor in a model, since due to collinearity problems, we do not want factors in a regression model to be highly correlated.

Table 4.1: Summary statistics for the factors used in the five models.

			Cross Correlations				
Factor Portfolio	Excess Return	Standard Deviation	Market	SMB	HML	RMW	CMA
Market	-0.002	0.091	1	0.045	0.08	-0.38	-0.10
SMB	0.016	0.038		1	-0.36	-0.67	0.41
HML	0.010	0.027			1	0.42	-0.08
RMW	-0.001	0.025				1	-0.50
CMA	0.003	0.016					1

The table reports the summary statistics for factors used in the five models. The return data are monthly data with dividends reinvested. All returns are net of expenses. The study period is December 2010 to March 2015.

4.3 The Performance Analysis

4.3.1 Results and Discussions

Table 4.2 reports the regression results for each of the five models. But here we focus on the two-factor model containing the market and a size factor–our optimal model. We chose this model as our best model to use as a benchmark for mutual fund performance as explained in Chapter 2. The first column shows the model we used as the benchmark, the second column shows the average annualized alpha, the third column is the β of the market, and the fourth column is the β of the SMB factor. The eighth column is the adjusted R-squared and the last column shows the percentages of α that are statistically positive, not different from zero and statistically negative. At the first glance, the figures in all columns indicate that the Chinese mutual funds returns behaved in accordance with other similar emerging countries and that the two-factor model explained the funds' returns well. The annualized α is -5.35%, which indicates the funds as a group underperformed the benchmark. The factor loading (β) of the market is 0.8, indicating the market factor, as expected, is the main factor that explains the funds' returns. The significant factor loading on SMB indicates that the returns of the funds were being driven relatively more by small stocks. The α distribution in the last column shows that 12% of funds showed statistically significant positive returns. The portion of statistically negative α is much larger at 24%.

To observe whether the macro-economic conditions influenced the model's explanation power, we split the time period into two halves. Table 4.3 shows the regression results from the same five models in the two split periods of December 2006 to December 2012, and January 2013 to December 2016[4]. Again, for now,

[4]We split the period this way simply because the first sub-period was under turbulent macro-economic conditions and the second sub-period was under normal macro-economic conditions.

we focus on our optimal model here. The results are somewhat interesting. Even though the αs are still negative, the α for the second period (2012 to 2016) are much more severe. The factor loading for SMB is also much bigger for the second period. The combination of these two facts indicates that fund managers are more prone to investing in small stocks. As a result, it is necessary to include an SMB factor in the benchmark model. This phenomenon sheds some light upon why some studies find a three-factor model does not show significant αs in the Chinese mutual fund market. One possible reason for the three-factor model not showing statistically significant explanatory power in explaining Chinese mutual fund returns is that the two factors (the SMB and HML) are in fact highly negatively correlated, which cancels out the power of each of the two factors. When, the HML is removed from the model, one would find that the resulting two- factor model does have explanatory power in mutual fund returns.

4.3.2 Robustness Check Using Alternative Models

Even though we concluded the two-factor model containing the market factor and an SMB factor was the most appropriate model to use as a benchmark for analyzing mutual fund risk adjusted performance, in this section we still compare the regression results produced by (1) the CAPM model; (2) a two-factor model containing the market and HML factors; (3) a Fama French three-factor model containing the market, SMB and HML factors; and (4) a five factor model containing the market, SMB, HML, the RMW and the CMA factors. Table 4.2 shows the aggregate regression results from these four models. Surprisingly, all annualized αs produced by the four alternative models were positive, which is contrary to the αs produced by our chosen best two-factor model (market and SMB). The second highest annualized α was produced by the CAPM model. This indicates that the CAPM is not suitable as a benchmark to judge the performance, which is also confirmed by the lowest adjusted R-Squared. The Fama French three-factor model produced the lowest annualized α among the four alternative models (0.9%). However, including an HML factor offset the explanation power of the SMB factor because of their high negative correlations.

Again, we split the study period into two periods and compared the difference in regression results. As shown in Table 4.3, the CAPM produces very different annualized α in the 2007 to 2011 period and 2012 to 2016 period. In the early period of 2007 to 2011, the annualized α produced by CAPM was only 0.46%, while in the later period 2012 to 2016 the α was 6.29%. Coupled with the fact that the adjusted R-squared was 77.65% in 2007 to 2011 and only 63.29% in 2012 to 2016, we suspect that Chinese mutual fund managers increased holdings of risky assets that are small and with low book-to-market ratio. The return of these risky assets is not captured by the CAPM model; therefore, a simple CAPM model produced a high α in the period 2012 to 2016. This implies that during this period, the CAPM did not capture the characteristics of the stocks the fund managers holds in China.

Looking at both Tables 4.2 and 4.3, an interesting phenomenon emerges: the models including and excluding the SMB factors produce dramatically different results both during the whole period displayed in Table 4.2 and in the split periods in Table 4.3. In particular, once the SMB is included in a model, the model produces a much lower α than the models that exclude it. For example, during the complete period, all models except the two-factor models containing the market factor and a SMB factor produced positive average α. This fact is more dramatic in the second split period in Table 4.3 where both the CAPM and the Fama-French three-factor model produced relatively high positive α (6.29% and 7.18% per year), yet a two-factor model ($Market + SMB$) produced a strong negative α (-8.75% per year). This confirmed that the SMB has a strong explanatory power in explaining mutual fund return variations and should be included in a model. Excluding the SMB would produce a distorted picture about fund managers' stock-picking ability. In particular, these models would give a distorted conclusion that the managers have stock selection ability, while they really were just holding a large amount of small stocks.

Looking through Table 4.3, we can see that all models except the two-factor model (Market+SMB) produced improved annual average αs in the second period compared with the first period, which would easily imply that managers in China are getting more accurate at picking the potentially high-performing stocks. However, when we apply the two-factor model (Market + SMB), the true picture appeared. This two-factor model (Market +SMB) produced a much stronger negative average α in the second sub-period than in the first sub-period. We suspect that the reason the managers appeared to be able to pick high-performance stocks is that they simply started holding more small stocks in their portfolios which are highly risky (volatile).

To summarize, all four alternative models examined in this section for robustness indicated that managers have superb stock-picking ability which is contrary to what the two-factor model containing a market and a size factor indicated. The loading on the SMB factor suggests that the fund managers on the aggregate level hold more small stocks than big stocks, which made their investment more risky. The popular three-factor model would easily result in a misleading conclusion, since the HML factor is highly negatively correlated with the SMB factor. Selecting a wrong model to analyze mutual fund performance is detrimental to investors, since all the wrong models gave very good pictures about managers' performance.

Table 4.2: Summary regression statistics of the models containing a CAPM, two-factor, a three-factor and a five-factor models.

	α_{annual}	β_{Market}	β_{SMB}	β_{HML}	β_{RMW}	β_{CMA}	R^2_{adj}	α Distribution (as %) +/0/-
CAPM	4.61%	0.80					65.28%	19/81/0
Market+SMB	-5.35%	0.80	0.52				74.38%	12/64/24
Market+HML	5.29%	0.83		-0.68			77.65%	34/66/0
Market+SMB+HML	0.93%	0.82	0.26	-0.52			78.59%	15/82/3
Market+SMB+HML+RMW+CMA	1.68%	0.81	0.24	-0.47	-0.11	-0.35	79.22%	15/83/2

The Table reports the summary regression statistics of the models containing the CAPM, two two-factor, a three-factor and a five-factor models. The study period is December 2007 to December 2016.

Table 4.3: Summary regression statistics of the models containing the CAPM, two two-factor models, a three-factor model and a five factor model for the two sub periods of December 2006 to December 2011 and January 2012 to December 2016.

	α	β_{Market}	β_{SMB}	β_{HML}	β_{RMW}	β_{CMA}	R^2_{adj}	α Distributions (as %) +/0/-
2007-2011								
Market	0.46%	0.76					77.65%	9/91/0
Market+SMB	-1.35%	0.76	0.20				80.44%	11/81/8
Market+HML	0.40%	0.75		-0.29			81.80%	12/76/12
Market+SMB+HML	-0.55%	0.75	0.11	-0.23			82.49%	12/76/12
Market+SMB+HML+RMW+CMA	-1.02%	0.75	0.16	-0.24	-0.03	-0.37	83.97%	12/69/19
2012-2016								
Market	6.29%	0.85					63.29%	19/81/0
Market+SMB	-8.75%	0.84	0.66				76.16%	12/58/30
Market+HML	7.18%	0.89		-0.80			80.72%	12/70/18
Market+SMB+HML	1.78%	0.88	0.23	-0.63			81.54%	11/59/30
Market+SMB+HML+RMW+CMA	2.4%	0.87	0.20	-0.60	-0.05	-0.18	81.70%	12/70/18

Table 4.4: Fund returns before and after fees.

	After fees	Before fees
Market	4.61%	5.90%
Market+SMB	-5.35%	-4.06%
Market+HML	5.29%	6.58%
Market+SMB+HML	0.93%	2.22%
Market+SMB+HML+RMW+CMA	1.68%	2.97%

The fund performance before and after fees. The returns are annualized.

4.3.3 Management Fees

Since we have been examining fund returns using the monthly prices, the returns are net of management fees, which means the management fees are deducted from the fund returns. Management fees are an interesting topic in mutual fund research (see more detailed literature on this topic in Section 1.2.1). The most interesting finding was for the US market. Researchers found that the US fund managers are able to provide small positive returns for their investors. However, once the management fees were deducted, the returns for the investors were not statistically different from simply holding a passive market index. Nevertheless, there were contrary results in other markets. For example, Otten and Bams (2002) reported that in most European countries, fund managers were able to produce significant positive α even after fees were deducted.

Next, we examine and compare the returns before and after management fees. As shown in Table 4.4, they provided two results. The only benchmark that provides significant negative returns before and after fees was the two-factor model that contained the market and SMB factors. The other four models suggest significant positive abnormal returns. These two contrary results alert us to be extremely careful when deciding which model to use as an appropriate mutual fund performance benchmark.

4.3.4 Performance According to Fund Investment Style

Table 4.5 also examines funds with different investment styles, namely value funds (invested heavily in stocks with high book-to-market ratio), growth funds (invested heavily in stocks with low book-to-market ratio) and blend funds (invested in a mixture of stocks with high and low book-to-market ratio). The regression results from a two-factor model containing the market and HML factors indicates that value funds indeed invested most heavily in value stocks having an HML loading of -0.33, the highest of the three types of funds. Similarly, the growth funds indeed invest most heavily on growth stocks having a loading of -0.92, the lowest among the three types of funds. Interestingly, it was the blend funds that generated the highest α indicating that neither value strategy nor growth strategy has a stock-picking advantage in the Chinese equity mutual fund market.

Another insight that is reviewed by Table 4.5 is that the only model that consistently generated negative αs was the two-factor model (our best model) containing the market and size factor. In particular, using this model, the α was -8.20% for the growth funds, -0.87% for the value funds and -5.35% for the blend funds. All other models produced positive αs except the alpha produced by the three-factor model for the growth fund (-0.45%). This phenomenon confirms that if a wrong model is used, then a misleading results could be derived. In this case, the misleading result is that funds are performing much better than what they in fact are, after risk adjustment.

Table 4.5: Regression results of funds with different investment styles.

CAPM	α_{annual}	β_{Market}		
Growth funds	4.74	0.79		
Value funds	4.77	0.82		
Blend funds	4.93	0.80		
Two-factor model	α_{annual}	β_{Market}	β_{SMB}	
Growth funds	-8.20	0.78	0.69	
Value funds	-0.87	0.83	0.28	
Blend funds	-5.35	0.79	0.51	
Two-factor model	α_{annual}	β_{Market}		β_{HML}
Growth funds	5.24	0.82		-0.92
Value funds	5.23	0.83		-0.33
Blend funds	6.22	0.82		-0.70
Three-factor model	α_{annual}	β_{Market}	β_{SMB}	β_{HML}
Growth funds	-0.45	0.80	0.30	-0.71
Value funds	1.82	0.83	0.16	-0.23
Blend funds	1.80	0.82	0.21	-0.56

The table reports the regression results of funds with different investment styles using four models. The fund investment styles are growth funds, value funds and blend funds. The models used are (1) CAPM, (2) a two- factor model containing a market factor and a SMB factor, (3) a two-factor model containing a market factor and a HML factor, and (4) a Fama and French three-factor model.

4.4 The Influence of Fund Characteristics

The investigation of the influence of fund characteristics is the next step in our mutual fund returns analysis. Fund managers often claim management fees do not reduce fund performance, but the empirical evidence shows otherwise (Otten and Bams, 2002; Dahlquist et al., 2000; Białkowski and Otten, 2011). In this section, we examine the influence of a few key characteristics on the Chinese mutual fund performance.

The estimation model is:

$$\alpha_i = C_0 + C_1 Ln(\text{fees}) + C_2 Ln(\text{AssetSize}) + C_3 Ln(\text{Age}) + \epsilon_i \tag{4.6}$$

where α_i=α for fund i; fees=management fees for fund i; Asset Size=fund i's asset size; Age=fund i's age in months; C_0 is the intercept term; C_1 is the coefficient for the Ln(fees); C_2 is the coefficient for the Ln(AssetSize); C_3 is the coefficient for the Ln(Age).

Table 4.6 shows size and age have a strong relationship with funds' returns. The management fees have a positive relationship with funds' excess returns. The higher the management fees, the higher the fund's excess returns. In particular, if the fees increase by 1%, the α will go up by 0.02%. This relationship is consistent with what fund managers claim (they charge a high fee for high returns to investors) but contrary to the findings of Otten and Bams (2002) and Dahlquist et al. (2000). The second relationship is between fund size and α. The bigger the size, the higher the fund returns. In particular, if the Ln(AssetSize) increased by 0.01, the fund α will increase by 0.003%. This is contrary to the US market, where dis-economy of scale is apparent: once a fund grows too big, it is likely that the fund will be closed to new investors due to the lack of growth opportunities. It seems that in China, economy of scale is still available. This difference is also

Table 4.6: The influence of fund characteristics.

Constant	0.025***
Fees	0.002.
Asset size	0.003***
Age	-0.005***
adjusted R-Squared	0.30
p-value of regression	0.00

The influence of fund characteristics. Estimated using Equation 4.6 where α_i=α for fund i fees=ln of management fees for fund i Asset Size=ln of fund i's asset size Age=ln of fund i's age in months. Significant level of regressions' p-values: "***" p<0.001, "**" p<0.01, "*" p<0.05.

confirmed by Dahlquist et al. (2000) who finds good performance occurred among small asset under management equity funds. Finally, funds' age has a negative relationship with funds' returns. The older the fund, the lower the fund returns. In particular, if Ln(Age) goes up by 1, the fund return will drop by 0.005%. This is consistent with the findings in Otten and Bams (2002) that for all the countries studied, younger funds tend to perform better than older funds.

4.5 Summary and Conclusion

This chapter gives an overview of the Chinese mutual fund market and compares the results of mutual fund performance based on five different asset-pricing models. The models are the following:

1. The original CAPM model.
2. The two-factor model containing the market and size factor (SMB).
3. The two-factor model containing the market and book-to-market factor (HML).
4. The Fama and French three-factor model.
5. The Fama and French Five factor model.

We investigated whether the five models generated fundamentally different results. The findings of the chapter are interesting and important. Yet probably the most important set of results is in Table 4.5. The only model that consistently produced negative αs in the (1) whole period of December 2006 to December 2016 and (2) the two sub-periods of 2006 to 2011 and 2012 to 2016 was our best model that contained the market and size factors. The other four popular asset pricing models were not suitable to measure the risk adjusted mutual fund performance in China. A two-factor model containing the market and size factor (SMB) is better at explaining assets' returns and therefore measure equity mutual fund performance more appropriately. Failure to use the right model would generate serious misleading conclusions which not only ignore the risk behaviour of the fund managers but also give wrong impressions about the funds' performance to investors in China.

The management fees tells an interesting story (in Table 4.4): the level of negative risk adjusted returns is large. The funds on average have negative returns before and after management fees. Again, the only model that consistently produces this result is the two-factor model containing a market factor and an SMB factor. The other models produce inconsistent results, which remind us again of their inability to measure the risk adjusted fund performance in the unique Chinese mutual fund market.

In Section 4.3.3, we found the fund management fees and the funds' size are positively related to the funds' excess returns. The higher the fees and larger the fund, the higher the returns.

5. Conclusions and Future Research

5.1 Introduction

Since the early critique of the CAPM, a number of empirical studies have tried to find factor-style asset pricing models that aimed at better explaining the stock return variations. These include, but are not limited to, the Fama and French Three Factor Model (FF3), the Carhart Four Factor model and most recently, the Fama and French Five Factor model (FF5). The CAPM, FF3, and Carhart4 have been widely applied in markets all around the world, especially in the area of equity mutual fund performance analyses.

Nevertheless, these models were created using exclusively the data from the US market, yet are applied in domestic markets outside the US market, around the world. This created doubt regarding factors' ability to capture the true characteristics of these domestic stock markets, especially in special markets such as the Chinese stock markets. The work closest to investigating factors' explanatory power in a series of non-US domestic markets is Griffin (2002), which concluded that compared with international factors, domestic factors generally work well in explaining domestic market stock return variations. Yet, this paper ignored the Chinese markets. In the Chinese markets, we have evidence that the FF3 is not an appropriate model to explain stock return variations there. For example, on the aspect of factor loadings for the HML factor, Zhang and Xu (2014) reported that the HML factor has a positive sign in China; Guo and Wang (2014) reported that the HML has a negative sign in China; and Qi (2018) even claimed that the HML is not a factor at all there.

Recognizing this phenomenon, we were encouraged to conduct a series of investigations in this thesis, which attempted to find answers to the questions raised. The first question we had was: Within the range of the known five factors – the market factor, the SMB factor, the HML factor, the CMA factor and the RMW factor – what subset(s) would be most appropriate to explain stock return variations in the Chinese stock markets?

The second question has two parts: If and when the appropriate set of factors is found, would the model's explanatory power be increased further firstly by constructing the factors differently using the various methods specified in Fama and French (1993) and Fama and French (2015)? And by secondly redefining the cutting points for factors?

The most crucial question is the final question: Would using our optimal model fundamentally change the results of the performance evaluation of the mutual funds? Or, to put it more directly, would using a wrong asset pricing model produce misleading results in mutual fund performance analysis?

5.2 The First Question: What Subset(s) of Factors Explains the Stock Return Variations in China?

We answered the first question of what subset(s) of factors best explains the Chinese stock return variations by using monthly stock returns from the two stock exchanges (the Shanghai and Shenzhen stock exchanges) during the period between December 2006 to March 2017.

We constructed the necessary factors and ran a total of five regression models including the CAPM, a two factor model containing a market and a size factor, a two factor model containing a market and a book-to-market factor and a Fama and French three factor model and five factor model (see Chapter 2 for details).

We use the adjusted R^2 and the GRS test as our primary sources to judge models' performance. But at the end, when faced with three similar models, we used a subjective judgement and finally selected the two factor model containing the market factor and a size factor. We briefly describe the process of such selection below.

Judged from the adjusted R^2 and the GRS test, the more factors we included in our model, the higher the adjusted R^2 and the lower the GRS test score. Therefore, at first glance, the Fama and French five factor model could be the best. However, when combining the RMW with the market factor, or combining the CMA factor with the market factor, we found that the two new factors of FF5 do not add much explanatory power to the original FF3 here in China. The two new factors were discarded easily in the first step (see more details in Section 2.4 of Chapter 2.

The second model that got eliminated was the CAPM. As shown by the regression analysis, the models containing the SMB and/or the HML factors are definitely adding more explanatory powers to the original one-factor CAPM (see Section 2.4 of Chapter 2 for more details).

Then, we were left facing a set of three different models: a two factor model containing the market and the SMB factor; a two factor model containing a market and an HML factor; and finally, a Fama and French three factor model containing a market, an SMB and an HML factor (FF3).

A clear decision then was made to discard the HML factor according to the following two reasons: firstly, the SMB and HML factors were highly correlated (see Table 2.3 of Chapter 2) and therefore, only one factor between these two should be kept in our optimal model. Secondly, the HML factor lacks accounting integrity due to the continuous change in accounting standards in China. Therefore, at the end, we decided that a two factor model containing a market and an SMB factor is our optimal model.

Unlike the problem in the US data, where the biggest problem of the model lay in the small-stock portfolios, our analyses suggest that our optimal model had trouble explaining the bigger-stock portfolios.

5.3 The Second Question: A Sensitivity Analysis on Breakpoints and Construction Methods

The second question was investigated in Chapter 3, which was essentially two sensitivity analyses. Fama and French (1993) and Fama and French (2015) investigated three different construction methods, namely 2×3, 2×2, and $2 \times 2 \times 2 \times 2$ (see Section 3.1.2 of Chapter 3 for details).

These questions are important. The Chinese stock markets are unusual. Firstly, due to financial market reforms, a large number of micro-small stocks suddenly appeared in the market, and these firms function fundamentally differently from the firms in the rest of the markets, especially from the big firms. By systematically testing the breakpoints for the size factor, we will be able to detect at what level of size the firms start to behave differently.

We report that using five different sorting/construction methods as specified in Table 3.5 that the regression results do not show statistically significant differences. Since in China, we decided to include only the market and the size in our optimal model, a simple 2×2 sort on size-B/M is sufficient and time saving.

When it comes to the second sensitivity analysis: the systematic testing of breakpoints for the size factor, we report the 50% – 50% is as good as it can be. Although a 60% – 40% (60% small, 40% big) provided a slightly better adjusted R^2, the improvement is, however small, and should be ignored for consistency with the well-known breakpoint of 50% – 50%.

5.4 The Third Question: Did Our Optimal Model Produce Fundamentally Different Results?

The third and last question on the model's application on mutual fund performance is an interesting question. To try to answer it, we used a total of five different asset pricing models, including our optimal model, to evaluate the Chinese mutual fund performance (see Chapter 4 for more details). We then compared these results to investigate whether these results were consistent despite the model used. In other words, we wanted to find out if our optimal model produces results that are fundamentally different from other traditional models.

As explained in Chapter 2, one of the applications of asset pricing models is to analyze equity's, that is, mutual funds' risk-adjusted performance. To analyze a fund's risk adjusted performance, the right set of factors on the RHS was regressed on the LHS mutual funds' returns. Therefore, using a wrong set of factors on the RHS could be misleading, which is especially detrimental to young markets like the ones in China, since most investors there have little or no education on financial products.

We used simultaneously the five models to regress mutual funds' performance for the period between December 2016 and March 2017. Interestingly, the only model that, over time, consistently produced negative αs was our optimal two factor model containing a market and a size factor (see Tables 4.2 and 4.3 in Chapter 4 for more details). This finding has important two-fold implications: Firstly, using traditional popular models, such as CAPM or the Fama and French three- factor model, will produce a result that says fund managers are doing well at picking stocks in the Chinese mutual fund market, which is misleading. Secondly, the evidence we have indicates that fund managers in China do hold large amounts of risky small stocks in their portfolios.

5.5 Limitations and Possible Future Research

5.5.1 Limitations

There are some limitations in this thesis, thus leaving rooms for future researches:

1. We concluded in our study that the HML factor, which was constructed using the B/M, was unreliable and should be discarded. However, the credibility of such claim may be questionable. We could have dug deeper into this issue by either trying alternative ratios that represents the B/M more accurately.

We suspect the biggest problem comes from the value for the "book value" of a company. We think the book value is especially unreliable because it is calculated from the difference between a company's liabilities and assets. We could have examined the book value deeper by looking into the liabilities and assets, for example, by deducting accounts payable and accounts receivable from the liability and the assets to get a net figure better representing the true levels of liability and assets. But at the end, to get to the bottom of this required more time and effort.

2. The problem of our model lies in the large size and high B/M portfolios (see Section 2.4.1 of Chapter 2). This indicates that extremely large and high B/M

firms behave differently from the rest of the firms in the stock markets. These large firms are typically highly influenced by the government, and their extremely high B/M ratio could indicate that their book value is either miscalculated or contains negative information which is well known among investors, who then self-correct firms' expected future returns.

5.5.2 Future Research

There is also material in this thesis that can be carried out by further research:

1. While considering the momentum factor, a preliminary analysis indicated that the momentum is "U"-shaped in China, at which point we discarded the momentum factor in our analyses (see Section A.1 for details). To investigate this "U"-shaped momentum factor further, if mutual fund holding information were available, we would have been able to thoroughly investigate the detailed strategies held by the fund managers and explain why the funds' returns are "U"-shaped.

2. Investigating the true nature of the B/M, and therefore the HML factor requires a large effort. Someone could even look at different time periods to see whether the explanatory power of HML increases over time because of accounting reforms resulting in improved accounting standards.

A. Appendix on The Momentum Factor

A.1 The Momentum Factor

Persistence analysis is a common aspect of mutual fund performance analysis, which has the same logic as the momentum strategy. If a fund's return is said to be "persistent", it means this fund had a high return in the previous period and this high return has been found to continue in the following period. This effect is vividly likened to a "hot hand" effect (Otten and Bams, 2002).

In the literature, this effect has been investigated in many countries. Even though in an early study by Jensen (1968), which claimed there was not enough evidence of persistence in α, yet from the early 1990s, people started to see evidence of persistence in mutual fund returns. Grinblatt and Titman (1989) and Hendricks et al. (1993) found evidence of α in either short- and long-term horizons.

Table A.1 reveals the persistence of fund returns in China. All funds' monthly returns are ranked from high return to low return based on the previous six months' returns. Then they are allocated into seven portfolios. Portfolio 1A contains the top 20% funds and portfolio 4B contains the bottom 20% funds. From portfolio 1A to 4B, the returns of the previous six months move from high

Table A.1: Summary of persistence analysis. Also refer to Figure A.1

Ranked Portfolios	Excess returns	stdev	α	Market	SMB	HML	R^2
1A (High)	0.15	2.16	-0.78	-0.07	0.05	-0.08	0.03
1B	-0.15	2.82	-1.10	-0.12	0.09	-0.06	0.06
1	-0.34	3.12	-1.31	-0.13	0.12	-0.06	0.07
2	-0.31	2.92	-1.26	-0.12	0.11	-0.06	0.07
3	-0.25	3.18	-1.21	-0.12	0.11	-0.06	0.05
4A	-0.07	3.01	-0.99	-0.10	0.09	-0.10	0.06
4B	0.08	2.88	-0.90	-0.09	0.11	-0.05	0.04

All funds' monthly returns are ranked from high return to low return based on the previous six months' returns. Then they are allocated into seven portfolios. Portfolio 1A contains top 20 funds, portfolio 4B contains bottom 20 funds. From portfolio 1A to 4B, returns of previous six months moves from high level to low level. We then hold all seven portfolios for six months and calculate the average excess returns for the following six months. Note that the portfolios are reconstructed at the end of each month.

to low. We then observe the returns of these seven portfolios for six months and calculate the average excess returns for the following six months. Note that the portfolios are reconstructed at the end of each month.

As can be seen in Table A.1, the excess returns of the portfolio with the top previous six months' returns also generated the highest average returns in the following six months (0.15% per month). Looking at the descending portfolios 1B to 4B, the following six months' returns appears to be "U"-shaped (Figure A.1), that is, the returns drop first and then recovers (0.15%, -0.34%, -0.31%, -0.25%, -0.07% and 0.08%). The portfolios with the highest previous returns produce high returns in the following period; the portfolios with the lowest previous returns also produce high returns in the following period. The medium portfolios, however, generate lower returns in the following period. This phenomenon explains why the momentum is not a strong factor that explains the Chinese stock returns, because the returns produced by the top and bottoms portfolios both generate high returns which offset each other.

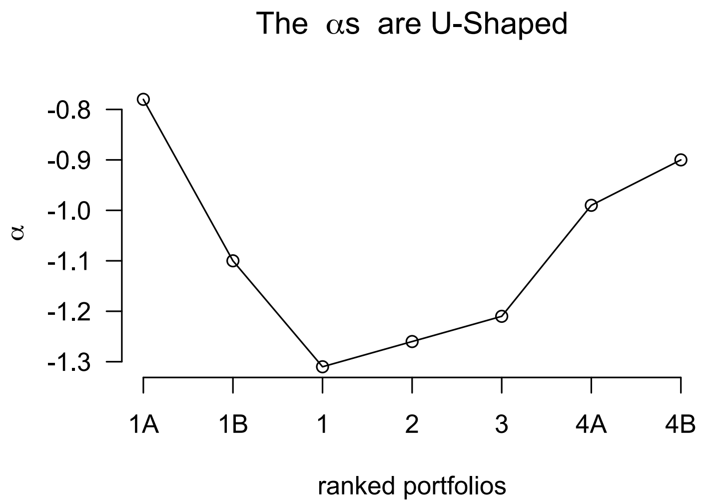


Figure A.1: Graphical presentation of column four in Table A.1. As can be seen, the αs are U-shaped.

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